

Lecture Notes for Linear Algebra

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Fall 2010

preface

These notes should cover the material in lecture at a minimum. Sometimes I may refer to the notes rather than write out certain lengthy theorems or definitions, it would be good if you had a copy of these notes for your convenience, I've seen students fit as many as 6 pages to a single side of paper, if your eyesight is good it's not much to carry. I do expect you come to class. Attending class is a necessary, but not sufficient condition for success in this course. You will need to spend time outside class pondering what was said. I would recommend you form a study group to work on the homework and/or study together. If you're like me then you'll want to try the homework before joining the group. Also, there are easily 100 pages of solutions from the previous text we used at LU by Insel, Spence and Freedberg. Those solutions provide you an additional bank of examples beyond my notes and your text. Don't forget they're there.

Doing the homework is doing the course. I cannot overemphasize the importance of thinking through the homework. I would be happy if you left this course with a working knowledge of:

- ✓ how to solve a system of linear equations
- ✓ Gaussian Elimination and how to interpret the $rref(A)$
- ✓ concrete and abstract matrix calculations
- ✓ determinants
- ✓ real vector spaces both abstract and concrete
- ✓ subspaces of vector space
- ✓ how to test for linear independence
- ✓ how to prove a set spans a space
- ✓ coordinates and bases
- ✓ column, row and null spaces for a matrix
- ✓ basis of an abstract vector space
- ✓ linear transformations
- ✓ matrix of linear transformation
- ✓ change of basis on vector space
- ✓ Eigenvalues and Eigenvectors
- ✓ Diagonalization
- ✓ geometry of Euclidean Space

- ✓ orthogonal bases and the Gram-Schmidt algorithm
- ✓ least squares fitting of experimental data
- ✓ best fit trigonometric polynomials (Fourier Analysis)
- ✓ principle axis theorems for conic sections and quadric surfaces

I hope that I have struck a fair balance between pure theory and application. Generally speaking, I tried to spread out the applications so that if you hate the theoretical part then there is still something fun in every chapter. However, the focus of these notes (and this course) is mathematics. It's good if you enjoy applications, but how can you rightly apply what you do not know? Part of the reason we chose the text by Lay is that it has a multitude of applications from economics to computer graphics to biology to electrical engineering. I will not cover most of those applications in lecture, nor will most appear on tests. However, you will have the option of reading those sections and working out problems for bonus credit. In fact, there are about 50 bonus problems I have selected from Lay. If you did all of them correctly then it could raise your score by about 1/2 a letter grade. The bonus work will be due for the whole semester on the last day of classes. Given that the required homework has 188 problems (each worth 1pt) you should deduce that not doing the regular homework means you cannot make more than a B in the course. The homework is not optional. Do not stay in this course unless you intend to do the majority of the homework. Thanks!

Before we begin, I should warn you that I assume quite a few things from the reader. These notes are intended for someone who has already grappled with the problem of constructing proofs. I assume you know the difference between \Rightarrow and \Leftrightarrow . I assume the phrase "iff" is known to you. I assume you are ready and willing to do a proof by induction, strong or weak. I assume you know what \mathbb{R} , \mathbb{C} , \mathbb{Q} , \mathbb{N} and \mathbb{Z} denote. I assume you know what a subset of a set is. I assume you know how to prove two sets are equal. I assume you are familiar with basic set operations such as union and intersection (although we don't use those much). More importantly, I assume you have started to appreciate that mathematics is more than just calculations. Calculations without context, without theory, are doomed to failure. At a minimum theory and proper mathematics allows you to communicate analytical concepts to other like-educated individuals.

Some of the most seemingly basic objects in mathematics are insidiously complex. We've been taught they're simple since our childhood, but as adults, mathematical adults, we find the actual definitions of such objects as \mathbb{R} or \mathbb{C} are rather involved. I will not attempt to provide foundational arguments to build numbers from basic set theory. I believe it is possible, I think it's well-thought-out mathematics, but we take the existence of the real numbers as an axiom for these notes. We assume that \mathbb{R} exists and that the real numbers possess all their usual properties. In fact, I assume \mathbb{R} , \mathbb{C} , \mathbb{Q} , \mathbb{N} and \mathbb{Z} all exist complete with their standard properties. In short, I assume we have numbers to work with. We leave the rigorization of numbers to a different course.

These notes are offered for the Fall 2010 semester at Liberty University. In large part they are simply a copy of last years notes, however I have changed the order of the material significantly in

several places. In particular, I have woven the material on linear transformations throughout several chapters and I have introduced the concept of linear independence and spanning earlier in the course. Eigenvectors are also introduced before the chapter on Euclidean geometry. Finally, I have relegated the material on systems of differential equations to a stand-alone chapter. I now cover a good portion of that material in Math 334. I still believe that the problem of solving $\frac{d\vec{x}}{dt} = A\vec{x}$ via generalized eigenvectors and the matrix exponential is a beautiful piece of algebra and analysis, but I wanted to free up time for covering factorization schemes this semester. New to these notes is added discussion of the LU, and (possibly) the singular, QR and spectral decompositions.

I like the text by Lay, however I do think theoretically it must be missing some bits and pieces here and there. I would ask you follow the logic in my notes primarily. In particular, I would like for you to use my definitions on tests. In homework you may use either my notes or Lay, provided you do not circumvent the purpose of the problem. For example: Problem: "use theorem X in this section to show sky is blue", if your answer is "you show in the notes that the sky is blue, so there." then I wouldn't expect much credit. Also, definitions are important, if I ask for the definition I don't want an equivalent statement or how to calculate it, I want the definition. But, how will you know what "the" definition is? Simple, READ.

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Chapter 1

Gauss-Jordan elimination

Gauss-Jordan elimination is an optimal method for solving a system of linear equations. Logically it may be equivalent to methods you are already familiar with but the matrix notation is by far the most efficient method. This is important since throughout this course we will be faced with the problem of solving linear equations. Additionally, the Gauss-Jordan produces the *reduced row echelon form*(rref) of the matrix. Given a particular matrix the rref is unique. This is of particular use in theoretical applications.

1.1 systems of linear equations

Let me begin with a few examples before I state the general definition.

Example 1.1.1. Consider the following system of 2 equations and 2 unknowns,

$$x + y = 2$$

$$x - y = 0$$

Adding equations reveals $2x = 2$ hence $x = 1$. Then substitute that into either equation to deduce $y = 1$. Hence the solution $(1, 1)$ is **unique**

Example 1.1.2. Consider the following system of 2 equations and 2 unknowns,

$$x + y = 2$$

$$3x + 3y = 6$$

We can multiply the second equation by $1/3$ to see that it is equivalent to $x + y = 2$ thus our two equations are in fact the same equation. There are infinitely many equations of the form (x, y) where $x + y = 2$. In other words, the solutions are $(x, 2 - x)$ for all $x \in \mathbb{R}$.

Both of the examples thus far were **consistent**.

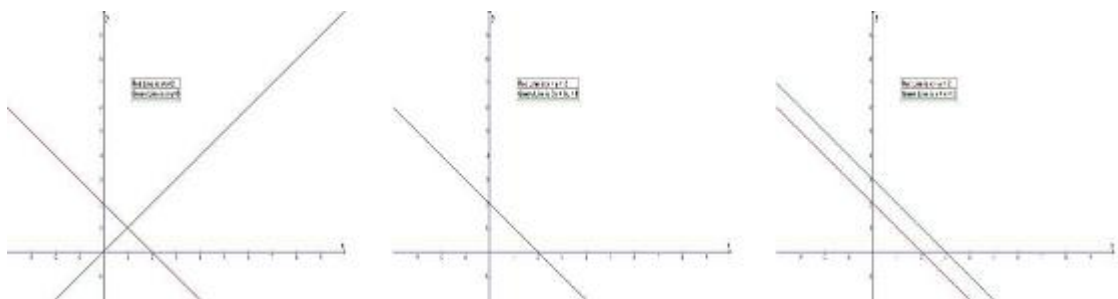
Example 1.1.3. Consider the following system of 2 equations and 2 unknowns,

$$x + y = 2$$

$$x + y = 3$$

These equations are inconsistent. Notice subtracting the second equation yields that $0 = 1$. This system has no solutions, it is **inconsistent**

It is remarkable that these three simple examples reveal the general structure of solutions to linear systems. Either we get a unique solution, infinitely many solutions or no solution at all. For our examples above, these cases correspond to the possible graphs for a pair of lines in the plane. A pair of lines may intersect at a point (unique solution), be the same line (infinitely many solutions) or be parallel (inconsistent).¹



Remark 1.1.4.

It is understood in this course that $i, j, k, l, m, n, p, q, r, s$ are in \mathbb{N} . I will not belabor this point. Please ask if in doubt.

Definition 1.1.5. system of m -linear equations in n -unknowns

Let x_1, x_2, \dots, x_n be n variables and suppose $b_i, A_{ij} \in \mathbb{R}$ for $1 \leq i \leq m$ and $1 \leq j \leq n$ then

$$A_{11}x_1 + A_{12}x_2 + \cdots + A_{1n}x_n = b_1$$

$$A_{21}x_1 + A_{22}x_2 + \cdots + A_{2n}x_n = b_2$$

$$\vdots \quad \vdots \quad \vdots \quad \vdots$$

$$A_{m1}x_1 + A_{m2}x_2 + \cdots + A_{mn}x_n = b_m$$

is called a **system of linear equations**. If $b_i = 0$ for $1 \leq i \leq m$ then we say the system is **homogeneous**. The **solution set** is the set of all $(x_1, x_2, \dots, x_n) \in \mathbb{R}^n$ which satisfy all the equations in the system simultaneously.

¹I used the *Graph* program to generate these graphs. It makes nice pictures, these are ugly due to user error.

Remark 1.1.6.

We use variables x_1, x_2, \dots, x_n mainly for general theoretical statements. In particular problems and especially for applications we tend to defer to the notation x, y, z etc...

Definition 1.1.7.

The augmented coefficient matrix is an array of numbers which provides an abbreviated notation for a system of linear equations.

$$\left[\begin{array}{cccc|c} A_{11}x_1 + A_{12}x_2 + \cdots + A_{1n}x_n = b_1 \\ A_{21}x_1 + A_{22}x_2 + \cdots + A_{2n}x_n = b_2 \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ A_{m1}x_1 + A_{m2}x_2 + \cdots + A_{mn}x_n = b_m \end{array} \right] \quad \text{abbreviated by} \quad \left[\begin{array}{cccc|c} A_{11} & A_{12} & \cdots & A_{1n} & b_1 \\ A_{21} & A_{22} & \cdots & A_{2n} & b_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{mn} & b_m \end{array} \right].$$

The vertical bar is optional, I include it to draw attention to the distinction between the matrix of coefficients A_{ij} and the nonhomogeneous terms b_i . Let's revisit my three simple examples in this new notation. I illustrate the Gauss-Jordan method for each.

Example 1.1.8. The system $x + y = 2$ and $x - y = 0$ has augmented coefficient matrix:

$$\begin{aligned} & \left[\begin{array}{cc|c} 1 & 1 & 2 \\ 1 & -1 & 0 \end{array} \right] \xrightarrow{r_2 - r_1 \rightarrow r_2} \left[\begin{array}{cc|c} 1 & 1 & 2 \\ 0 & -2 & -2 \end{array} \right] \\ & \xrightarrow{r_2 / -2 \rightarrow r_2} \left[\begin{array}{cc|c} 1 & 1 & 2 \\ 0 & 1 & 1 \end{array} \right] \xrightarrow{r_1 - r_2 \rightarrow r_1} \left[\begin{array}{cc|c} 1 & 0 & 1 \\ 0 & 1 & 1 \end{array} \right] \end{aligned}$$

The last augmented matrix represents the equations $x = 1$ and $y = 1$. Rather than adding and subtracting equations we added and subtracted rows in the matrix. Incidentally, the last step is called the **backward pass** whereas the first couple steps are called the **forward pass**. Gauss is credited with figuring out the forward pass then Jordan added the backward pass. Calculators can accomplish these via the commands *ref* (Gauss' row echelon form) and *rref* (Jordan's reduced row echelon form). In particular,

$$\text{ref} \left[\begin{array}{cc|c} 1 & 1 & 2 \\ 1 & -1 & 0 \end{array} \right] = \left[\begin{array}{cc|c} 1 & 1 & 2 \\ 0 & 1 & 1 \end{array} \right] \quad \text{rref} \left[\begin{array}{cc|c} 1 & 1 & 2 \\ 1 & -1 & 0 \end{array} \right] = \left[\begin{array}{cc|c} 1 & 0 & 1 \\ 0 & 1 & 1 \end{array} \right]$$

Example 1.1.9. The system $x + y = 2$ and $3x + 3y = 6$ has augmented coefficient matrix:

$$\left[\begin{array}{cc|c} 1 & 1 & 2 \\ 3 & 3 & 6 \end{array} \right] \xrightarrow{r_2 - 3r_1 \rightarrow r_2} \left[\begin{array}{cc|c} 1 & 1 & 2 \\ 0 & 0 & 0 \end{array} \right]$$

The nonzero row in the last augmented matrix represents the equation $x + y = 2$. In this case we cannot make a backwards pass so the *ref* and *rref* are the same.

Example 1.1.10. The system $x + y = 3$ and $x + y = 2$ has augmented coefficient matrix:

$$\left[\begin{array}{cc|c} 1 & 1 & 3 \\ 1 & 1 & 2 \end{array} \right] \xrightarrow{r_2 - 3r_1 \rightarrow r_2} \left[\begin{array}{cc|c} 1 & 1 & 1 \\ 0 & 0 & 1 \end{array} \right]$$

The last row indicates that $0x + 0y = 1$ which means that there is no solution since $0 \neq 1$. Generally, when the bottom row of the $\text{rref}(A|b)$ is zeros with a 1 in the far right column then the system $Ax = b$ is inconsistent because there is no solution to the equation.

1.2 Gauss-Jordan algorithm

To begin we need to identify three basic operations we do when solving systems of equations. I'll define them for system of 3 equations and 3 unknowns, but it should be obvious this generalizes to m equations and n unknowns without much thought. The following operations are called **Elementary Row Operations**.

(1.) scaling row 1 by nonzero constant c

$$\left[\begin{array}{ccc|c} A_{11} & A_{12} & A_{13} & b_1 \\ A_{21} & A_{22} & A_{23} & b_2 \\ A_{31} & A_{32} & A_{33} & b_3 \end{array} \right] \xrightarrow{cr_1 \rightarrow r_1} \left[\begin{array}{ccc|c} cA_{11} & cA_{12} & cA_{13} & cb_1 \\ A_{21} & A_{22} & A_{23} & b_2 \\ A_{31} & A_{32} & A_{33} & b_3 \end{array} \right]$$

(2.) replace row 1 with the sum of row 1 and row 2

$$\left[\begin{array}{ccc|c} A_{11} & A_{12} & A_{13} & b_1 \\ A_{21} & A_{22} & A_{23} & b_2 \\ A_{31} & A_{32} & A_{33} & b_3 \end{array} \right] \xrightarrow{r_1 + r_2 \rightarrow r_1} \left[\begin{array}{ccc|c} A_{11} + A_{21} & A_{12} + A_{22} & A_{13} + A_{23} & b_1 + b_2 \\ A_{21} & A_{22} & A_{23} & b_2 \\ A_{31} & A_{32} & A_{33} & b_3 \end{array} \right]$$

(3.) swap rows 1 and 2

$$\left[\begin{array}{ccc|c} A_{11} & A_{12} & A_{13} & b_1 \\ A_{21} & A_{22} & A_{23} & b_2 \\ A_{31} & A_{32} & A_{33} & b_3 \end{array} \right] \xrightarrow{r_1 \longleftrightarrow r_2} \left[\begin{array}{ccc|c} A_{21} & A_{22} & A_{23} & b_2 \\ A_{11} & A_{12} & A_{13} & b_1 \\ A_{31} & A_{32} & A_{33} & b_3 \end{array} \right]$$

Each of the operations above corresponds to an allowed operation on a system of linear equations. When we make these operations we will not change the solution set. Notice the notation tells us what we did and also where it is going. I do expect you to use the same notation. I also expect you can figure out what is meant by $cr_2 \rightarrow r_2$ or $r_1 - 3r_2 \rightarrow r_1$. We are only allowed to make a finite number of the operations (1.), (2.) and (3.). The Gauss-Jordan algorithm tells us which order to make these operations in order to reduce the matrix to a particularly simple format called the "reduced row echelon form" (I abbreviate this rref most places). The following definition is borrowed from the text *Elementary Linear Algebra: A Matrix Approach*, 2nd ed. by Spence, Insel and Friedberg, however you can probably find nearly the same algorithm in dozens of other texts.

Definition 1.2.1. Gauss-Jordan Algorithm.

Given an m by n matrix A the following sequence of steps is called the Gauss-Jordan algorithm or Gaussian elimination. I define terms such as **pivot column** and **pivot position** as they arise in the algorithm below.

Step 1: Determine the leftmost nonzero column. This is a **pivot column** and the topmost position in this column is a **pivot position**.

Step 2: Perform a row swap to bring a nonzero entry of the pivot column below the pivot row to the top position in the pivot column (in the first step there are no rows above the pivot position, however in future iterations there may be rows above the pivot position, see 4).

Step 3: Add multiples of the pivot row to create zeros **below** the pivot position. This is called "clearing out the entries below the pivot position".

Step 4: If there is a nonzero row below the pivot row from (3.) then find the next pivot position by looking for the next nonzero column to the right of the previous pivot column. Then perform steps 1-3 on the new pivot column. When no more nonzero rows below the pivot row are found then go on to step 5.

Step 5: the leftmost entry in each nonzero row is called the **leading entry**. Scale the bottommost nonzero row to make the leading entry 1 and use row additions to clear out any remaining nonzero entries **above** the leading entries.

Step 6: If step 5 was performed on the top row then stop, otherwise apply Step 5 to the next row up the matrix.

Steps (1.)-(4.) are called the **forward pass**. A matrix produced by a forward pass is called the *reduced echelon form* of the matrix and it is denoted $\text{ref}(A)$. Steps (5.) and (6.) are called the **backwards pass**. The matrix produced by completing Steps (1.)-(6.) is called the *reduced row echelon form* of A and it is denoted $\text{rref}(A)$.

The $\text{ref}(A)$ is not unique because there may be multiple choices for how Step 2 is executed. On the other hand, it turns out that $\text{rref}(A)$ is unique. The proof of uniqueness can be found in Appendix E of your text. The backwards pass takes the ambiguity out of the algorithm. Notice the forward pass goes down the matrix while the backwards pass goes up the matrix.

Example 1.2.2. Given $A = \begin{bmatrix} 1 & 2 & -3 & 1 \\ 2 & 4 & 0 & 7 \\ -1 & 3 & 2 & 0 \end{bmatrix}$ calculate $rref(A)$.

$$A = \left[\begin{array}{ccc|c} 1 & 2 & -3 & 1 \\ 2 & 4 & 0 & 7 \\ -1 & 3 & 2 & 0 \end{array} \right] \xrightarrow{r_2 - 2r_1 \rightarrow r_2} \left[\begin{array}{ccc|c} 1 & 2 & -3 & 1 \\ 0 & 0 & 6 & 5 \\ -1 & 3 & 2 & 0 \end{array} \right] \xrightarrow{r_1 + r_3 \rightarrow r_3} \left[\begin{array}{ccc|c} 1 & 2 & -3 & 1 \\ 0 & 0 & 6 & 5 \\ 0 & 5 & -1 & 1 \end{array} \right] \xrightarrow{r_2 \leftrightarrow r_3} \left[\begin{array}{ccc|c} 1 & 2 & -3 & 1 \\ 0 & 5 & -1 & 1 \\ 0 & 0 & 6 & 5 \end{array} \right] = ref(A)$$

that completes the forward pass. We begin the backwards pass,

$$ref(A) = \left[\begin{array}{ccc|c} 1 & 2 & -3 & 1 \\ 0 & 5 & -1 & 1 \\ 0 & 0 & 6 & 5 \end{array} \right] \xrightarrow{r_3 \leftarrow \frac{1}{6}r_3} \left[\begin{array}{ccc|c} 1 & 2 & -3 & 1 \\ 0 & 5 & -1 & 1 \\ 0 & 0 & 1 & 5/6 \end{array} \right] \xrightarrow{r_2 + r_3 \leftarrow r_2} \left[\begin{array}{ccc|c} 1 & 2 & -3 & 1 \\ 0 & 5 & 0 & 11/6 \\ 0 & 0 & 1 & 5/6 \end{array} \right] \xrightarrow{r_1 + 3r_3 \leftarrow r_1} \left[\begin{array}{ccc|c} 1 & 2 & 0 & 21/6 \\ 0 & 5 & 0 & 11/6 \\ 0 & 0 & 1 & 5/6 \end{array} \right] \xrightarrow{\frac{1}{5}r_2 \leftarrow r_2} \left[\begin{array}{ccc|c} 1 & 2 & 0 & 21/6 \\ 0 & 1 & 0 & 11/30 \\ 0 & 0 & 1 & 5/6 \end{array} \right] \xrightarrow{r_1 - 2r_2 \leftarrow r_1} \boxed{\left[\begin{array}{ccc|c} 1 & 0 & 0 & 83/30 \\ 0 & 1 & 0 & 11/30 \\ 0 & 0 & 1 & 5/6 \end{array} \right]} = rref(A)$$

Example 1.2.3. Given $A = \begin{bmatrix} 1 & -1 & 1 \\ 3 & -3 & 0 \\ 2 & -2 & -3 \end{bmatrix}$ calculate $rref(A)$.

$$A = \left[\begin{array}{ccc} 1 & -1 & 1 \\ 3 & -3 & 0 \\ 2 & -2 & -3 \end{array} \right] \xrightarrow{r_2 - 3r_1 \rightarrow r_2} \left[\begin{array}{ccc} 1 & -1 & 1 \\ 0 & 0 & -3 \\ 2 & -2 & -3 \end{array} \right] \xrightarrow{r_3 - 2r_1 \rightarrow r_3} \left[\begin{array}{ccc} 1 & -1 & 1 \\ 0 & 0 & -3 \\ 0 & 0 & -5 \end{array} \right] \xrightarrow{\begin{array}{l} 3r_3 \rightarrow r_3 \\ 5r_2 \rightarrow r_2 \end{array}} \left[\begin{array}{ccc} 1 & -1 & 1 \\ 0 & 0 & -15 \\ 0 & 0 & -15 \end{array} \right] \xrightarrow{\begin{array}{l} r_3 - r_2 \rightarrow r_3 \\ -\frac{1}{15}r_2 \rightarrow r_2 \end{array}} \left[\begin{array}{ccc} 1 & -1 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{array} \right] \xrightarrow{r_1 - r_2 \rightarrow r_1} \boxed{\left[\begin{array}{ccc} 1 & -1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{array} \right]} = rref(A)$$

Note it is customary to read multiple row operations from top to bottom if more than one is listed between two of the matrices. The multiple arrow notation should be used with caution as it has great potential to confuse. Also, you might notice that I did not strictly-speaking follow Gauss-Jordan in the operations $3r_3 \rightarrow r_3$ and $5r_2 \rightarrow r_2$. It is sometimes convenient to modify the algorithm slightly in order to avoid fractions.

Example 1.2.4. *easy examples are sometimes disquieting, let $r \in \mathbb{R}$,*

$$v = \begin{bmatrix} 2 & -4 & 2r \end{bmatrix} \xrightarrow{\frac{1}{2}r_1 \rightarrow r_1} \boxed{\begin{bmatrix} 1 & -2 & r \end{bmatrix} = rref(v)}$$

Example 1.2.5. *here's another next to useless example,*

$$v = \begin{bmatrix} 0 \\ 1 \\ 3 \end{bmatrix} \xrightarrow{r_1 \leftrightarrow r_2} \begin{bmatrix} 1 \\ 0 \\ 3 \end{bmatrix} \xrightarrow{r_3 - 3r_1 \rightarrow r_3} \boxed{\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = rref(v)}$$

Example 1.2.6. *Find the rref of the matrix A given below:*

$$\begin{aligned} A &= \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & 0 & 1 \\ -1 & 0 & 1 & 1 & 1 \end{bmatrix} \xrightarrow{r_2 - r_1 \rightarrow r_2} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & -2 & 0 & -1 & 0 \\ -1 & 0 & 1 & 1 & 1 \end{bmatrix} \xrightarrow{r_3 + r_1 \rightarrow r_3} \\ &\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & -2 & 0 & -1 & 0 \\ 0 & 1 & 2 & 2 & 2 \end{bmatrix} \xrightarrow{r_2 \leftrightarrow r_3} \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 2 & 2 & 2 \\ 0 & -2 & 0 & -1 & 0 \end{bmatrix} \xrightarrow{r_3 + 2r_2 \rightarrow r_3} \\ &\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 2 & 2 & 2 \\ 0 & 0 & 4 & 3 & 4 \end{bmatrix} \xrightarrow{\begin{smallmatrix} 4r_1 \rightarrow r_1 \\ 2r_2 \rightarrow r_2 \end{smallmatrix}} \begin{bmatrix} 4 & 4 & 4 & 4 & 4 \\ 0 & 2 & 4 & 4 & 4 \\ 0 & 0 & 4 & 3 & 4 \end{bmatrix} \xrightarrow{\begin{smallmatrix} r_2 - r_3 \rightarrow r_2 \\ r_1 - r_3 \rightarrow r_1 \end{smallmatrix}} \\ &\begin{bmatrix} 4 & 4 & 0 & 1 & 0 \\ 0 & 2 & 0 & 1 & 0 \\ 0 & 0 & 4 & 3 & 4 \end{bmatrix} \xrightarrow{r_1 - 2r_2 \rightarrow r_1} \begin{bmatrix} 4 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 1 & 0 \\ 0 & 0 & 4 & 3 & 4 \end{bmatrix} \xrightarrow{\begin{smallmatrix} r_1/4 \rightarrow r_1 \\ r_2/2 \rightarrow r_2 \\ r_3/4 \rightarrow r_3 \end{smallmatrix}} \\ &\boxed{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1/2 & 0 \\ 0 & 0 & 1 & 3/4 & 1 \end{bmatrix} = rref(A)} \end{aligned}$$

Example 1.2.7.

$$\begin{aligned}
[A|I] &= \left[\begin{array}{ccc|ccc} 1 & 0 & 0 & 1 & 0 & 0 \\ 2 & 2 & 0 & 0 & 1 & 0 \\ 4 & 4 & 4 & 0 & 0 & 1 \end{array} \right] \xrightarrow{\substack{r_2 - 2r_1 \rightarrow r_2 \\ r_3 - 4r_1 \rightarrow r_3}} \\
&\left[\begin{array}{ccc|ccc} 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 2 & 0 & -2 & 1 & 0 \\ 0 & 4 & 4 & -4 & 0 & 1 \end{array} \right] \xrightarrow{r_3 - 2r_2 \rightarrow r_3} \left[\begin{array}{ccc|ccc} 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 2 & 0 & -2 & 1 & 0 \\ 0 & 0 & 4 & 0 & -2 & 1 \end{array} \right] \xrightarrow{\substack{r_2/2 \rightarrow r_2 \\ r_3/4 \rightarrow r_3}} \\
&\boxed{\left[\begin{array}{ccc|ccc} 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & -1 & 1/2 & 0 \\ 0 & 0 & 1 & 0 & -1/2 & 1/4 \end{array} \right]} = rref[A|I]
\end{aligned}$$

Example 1.2.8.

$$\begin{aligned}
A &= \left[\begin{array}{cccc} 1 & 0 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 1 \\ 3 & 2 & 0 & 0 \end{array} \right] \xrightarrow{r_4 - 3r_1 \rightarrow r_4} \left[\begin{array}{cccc} 1 & 0 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 1 \\ 0 & 2 & -3 & 0 \end{array} \right] \xrightarrow{r_4 - r_2 \rightarrow r_4} \\
&\left[\begin{array}{cccc} 1 & 0 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 1 \\ 0 & 0 & -3 & 0 \end{array} \right] \xrightarrow{r_4 + r_3 \rightarrow r_4} \left[\begin{array}{cccc} 1 & 0 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 1 \\ 0 & 0 & 0 & 1 \end{array} \right] \xrightarrow{r_3 - r_4 \rightarrow r_3} \\
&\left[\begin{array}{cccc} 1 & 0 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 1 \end{array} \right] \xrightarrow{\substack{r_2/2 \rightarrow r_2 \\ r_3/3 \rightarrow r_3 \\ r_1 - r_3 \rightarrow r_1}} \boxed{\left[\begin{array}{cccc} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{array} \right]} = rref(A)
\end{aligned}$$

Proposition 1.2.9.

If a particular column of a matrix is all zeros then it will be unchanged by the Gaussian elimination. Additionally, if we know $rref(A) = B$ then $rref[A|0] = [B|0]$ where 0 denotes one or more columns of zeros.

Proof: adding nonzero multiples of one row to another will result in adding zero to zero in the column. Likewise, if we multiply a row by a nonzero scalar then the zero column is unaffected. Finally, if we swap rows then this just interchanges two zeros. Gauss-Jordan elimination is just a finite sequence of these three basic row operations thus the column of zeros will remain zero as claimed. \square

Example 1.2.10. Use Example 1.2.3 and Proposition 1.2.9 to calculate,

$$\text{rref} \left[\begin{array}{cccc|c} 1 & 0 & 1 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 3 & 1 & 0 \\ 3 & 2 & 0 & 0 & 0 \end{array} \right] = \left[\begin{array}{cccc|c} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{array} \right]$$

Similarly, use Example 1.2.5 and Proposition 1.2.9 to calculate:

$$\text{rref} \left[\begin{array}{cccc} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 3 & 0 & 0 & 0 \end{array} \right] = \left[\begin{array}{cccc} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right]$$

I hope these examples suffice. One last advice, you should think of the Gauss-Jordan algorithm as a sort of road-map. It's ok to take detours to avoid fractions and such but the end goal should remain in sight. If you lose sight of that it's easy to go in circles. Incidentally, I would strongly recommend you find a way to check your calculations with technology. Mathematica will do any matrix calculation we learn. TI-85 and higher will do much of what we do with a few exceptions here and there. There are even websites which will do row operations, I provide a link on the course website. All of this said, I would remind you that I expect you be able perform Gaussian elimination correctly and quickly on the test and quizzes without the aid of a graphing calculator for the remainder of the course. The arithmetic matters. Unless I state otherwise it is expected you show the details of the Gauss-Jordan elimination in any system you solve in this course.

Theorem 1.2.11.

Let $A \in \mathbb{R}^{m \times n}$ then if R_1 and R_2 are both Gauss-Jordan eliminations of A then $R_1 = R_2$. In other words, the reduced row echelon form of a matrix of real numbers is unique.

Proof: see Appendix E in your text for details. This proof is the heart of most calculations we make in this course. \square

1.3 classification of solutions

Surprisingly Examples 1.1.8, 1.1.9 and 1.1.10 illustrate all the possible types of solutions for a linear system. In this section I interpret the calculations of the last section as they correspond to solving systems of equations.

Example 1.3.1. Solve the following system of linear equations if possible,

$$\begin{aligned} x + 2y - 3z &= 1 \\ 2x + 4y &= 7 \\ -x + 3y + 2z &= 0 \end{aligned}$$

We solve by doing Gaussian elimination on the augmented coefficient matrix (see Example 1.2.2 for details of the Gaussian elimination),

$$\text{rref} \left[\begin{array}{ccc|c} 1 & 2 & -3 & 1 \\ 2 & 4 & 0 & 7 \\ -1 & 3 & 2 & 0 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & 0 & 0 & 83/30 \\ 0 & 1 & 0 & 11/30 \\ 0 & 0 & 1 & 5/6 \end{array} \right] \Rightarrow \begin{array}{l} x = 83/30 \\ y = 11/30 \\ z = 5/6 \end{array}$$

(We used the results of Example 1.2.2).

Remark 1.3.2.

The geometric interpretation of the last example is interesting. The equation of a plane with normal vector $\langle a, b, c \rangle$ is $ax + by + cz = d$. Each of the equations in the system of Example 1.2.2 has a solution set which is in one-one correspondance with a particular plane in \mathbb{R}^3 . The intersection of those three planes is the single point $(83/30, 11/30, 5/6)$.

Example 1.3.3. Solve the following system of linear equations if possible,

$$\begin{aligned} x - y &= 1 \\ 3x - 3y &= 0 \\ 2x - 2y &= -3 \end{aligned}$$

Gaussian elimination on the augmented coefficient matrix reveals (see Example 1.2.3 for details of the Gaussian elimination)

$$\text{rref} \left[\begin{array}{cc|c} 1 & -1 & 1 \\ 3 & -3 & 0 \\ 2 & -2 & -3 \end{array} \right] = \left[\begin{array}{ccc} 1 & -1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{array} \right]$$

which shows the system has no solutions. The given equations are inconsistent.

Remark 1.3.4.

The geometric interpretation of the last example is also interesting. The equation of a line in the xy -plane is $ax + by = c$, hence the solution set of a particular equation corresponds to a line. To have a solution to all three equations at once that would mean that there is an intersection point which lies on all three lines. In the preceding example there is no such point.

Example 1.3.5. Solve the following system of linear equations if possible,

$$\begin{aligned} x - y + z &= 0 \\ 3x - 3y &= 0 \\ 2x - 2y - 3z &= 0 \end{aligned}$$

Gaussian elimination on the augmented coefficient matrix reveals (see Example 1.2.10 for details of the Gaussian elimination)

$$\text{rref} \left[\begin{array}{ccc|c} 1 & -1 & 1 & 0 \\ 3 & -3 & 0 & 0 \\ 2 & -2 & -3 & 0 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right] \Rightarrow \boxed{\begin{array}{l} x - y = 0 \\ z = 0 \end{array}}$$

The row of zeros indicates that we will not find a unique solution. We have a choice to make, either x or y can be stated as a function of the other. Typically in linear algebra we will solve for the variables that correspond to the pivot columns in terms of the non-pivot column variables. In this problem the pivot columns are the first column which corresponds to the variable x and the third column which corresponds the variable z . The variables x, z are called **basic variables** while y is called a **free** variable. The solution set is $\{(y, y, 0) \mid y \in \mathbb{R}\}$; in other words, $x = y, y = y$ and $z = 0$ for all $y \in \mathbb{R}$.

You might object to the last example. You might ask why is y the free variable and not x . This is roughly equivalent to asking the question why is y the dependent variable and x the independent variable in the usual calculus. However, the roles are reversed. In the preceding example the variable x depends on y . Physically there may be a reason to distinguish the roles of one variable over another. There may be a clear cause-effect relationship which the mathematics fails to capture. For example, velocity of a ball in flight depends on time, but does time depend on the ball's velocity? I'm guessing no. So time would seem to play the role of independent variable. However, when we write equations such as $v = v_o - gt$ we can just as well write $t = \frac{v-v_o}{-g}$; the algebra alone does not reveal which variable should be taken as "independent". Hence, a choice must be made. In the case of infinitely many solutions, we customarily **choose** the pivot variables as the "dependent" or "basic" variables and the non-pivot variables as the "free" variables. Sometimes the word *parameter* is used instead of variable, it is synonymous.

Example 1.3.6. Solve the following (silly) system of linear equations if possible,

$$\begin{aligned} x &= 0 \\ 0x + 0y + 0z &= 0 \\ 3x &= 0 \end{aligned}$$

Gaussian elimination on the augmented coefficient matrix reveals (see Example 1.2.10 for details of the Gaussian elimination)

$$\text{rref} \left[\begin{array}{ccc|c} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 3 & 0 & 0 & 0 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right]$$

we find the solution set is $\{(0, y, z) \mid y, z \in \mathbb{R}\}$. No restriction is placed the free variables y and z .

Example 1.3.7. Solve the following system of linear equations if possible,

$$\begin{aligned}x_1 + x_2 + x_3 + x_4 &= 1 \\x_1 - x_2 + x_3 &= 1 \\-x_1 + x_3 + x_4 &= 1\end{aligned}$$

Gaussian elimination on the augmented coefficient matrix reveals (see Example 1.2.6 for details of the Gaussian elimination)

$$\text{rref} \left[\begin{array}{cccc|c} 1 & 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & 0 & 1 \\ -1 & 0 & 1 & 1 & 1 \end{array} \right] = \left[\begin{array}{cccc|c} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1/2 & 0 \\ 0 & 0 & 1 & 3/4 & 1 \end{array} \right]$$

We find solutions of the form $x_1 = 0$, $x_2 = -x_4/2$, $x_3 = 1 - 3x_4/4$ where $x_4 \in \mathbb{R}$ is free. The solution set is a subset of \mathbb{R}^4 , namely $\{(0, -2s, 1 - 3s, 4s) \mid s \in \mathbb{R}\}$ (I used $s = 4x_4$ to get rid of the annoying fractions).

Remark 1.3.8.

The geometric interpretation of the last example is difficult to visualize. Equations of the form $a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 = b$ represent volumes in \mathbb{R}^4 , they're called *hyperplanes*. The solution is parametrized by a single free variable, this means it is a line. We deduce that the three hyperplanes corresponding to the given system intersect along a line. Geometrically solving two equations and two unknowns isn't too hard with some graph paper and a little patience you can find the solution from the intersection of the two lines. When we have more equations and unknowns the geometric solutions are harder to grasp. Analytic geometry plays a secondary role in this course so if you have not had calculus III then don't worry too much. I should tell you what you need to know in these notes.

Example 1.3.9. Solve the following system of linear equations if possible,

$$\begin{aligned}x_1 + x_4 &= 0 \\2x_1 + 2x_2 + x_5 &= 0 \\4x_1 + 4x_2 + 4x_3 &= 1\end{aligned}$$

Gaussian elimination on the augmented coefficient matrix reveals (see Example 1.2.7 for details of the Gaussian elimination)

$$\text{rref} \left[\begin{array}{ccccc|c} 1 & 0 & 0 & 1 & 0 & 0 \\ 2 & 2 & 0 & 0 & 1 & 0 \\ 4 & 4 & 4 & 0 & 0 & 1 \end{array} \right] = \left[\begin{array}{ccccc|c} 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & -1 & 1/2 & 0 \\ 0 & 0 & 1 & 0 & -1/2 & 1/4 \end{array} \right]$$

Consequently, x_4, x_5 are free and solutions are of the form

$$\begin{aligned}x_1 &= -x_4 \\x_2 &= x_4 - \frac{1}{2}x_5 \\x_3 &= \frac{1}{4} + \frac{1}{2}x_5\end{aligned}$$

for all $x_4, x_5 \in \mathbb{R}$.

Example 1.3.10. Solve the following system of linear equations if possible,

$$\begin{aligned}x_1 + x_3 &= 0 \\2x_2 &= 0 \\3x_3 &= 1 \\3x_1 + 2x_2 &= 0\end{aligned}$$

Gaussian elimination on the augmented coefficient matrix reveals (see Example 1.2.8 for details of the Gaussian elimination)

$$\text{rref} \left[\begin{array}{ccc|c} 1 & 0 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 1 \\ 3 & 2 & 0 & 0 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{array} \right]$$

Therefore, there are no solutions.

Example 1.3.11. Solve the following system of linear equations if possible,

$$\begin{aligned}x_1 + x_3 &= 0 \\2x_2 &= 0 \\3x_3 + x_4 &= 0 \\3x_1 + 2x_2 &= 0\end{aligned}$$

Gaussian elimination on the augmented coefficient matrix reveals (see Example 1.2.10 for details of the Gaussian elimination)

$$\text{rref} \left[\begin{array}{cccc|c} 1 & 0 & 1 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 3 & 1 & 0 \\ 3 & 2 & 0 & 0 & 0 \end{array} \right] = \left[\begin{array}{cccc|c} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{array} \right]$$

Therefore, the unique solution is $x_1 = x_2 = x_3 = x_4 = 0$. The solution set here is rather small, it's $\{(0, 0, 0, 0)\}$.

1.4 applications to curve fitting and circuits

We explore a few fun simple examples in this section. I don't intend for you to master the outs and in's of circuit analysis, those examples are for site-seeing purposes.²

Example 1.4.1. Find a polynomial $P(x)$ whose graph $y = P(x)$ fits through the points $(0, -2.7)$, $(2, -4.5)$ and $(1, 0.97)$. We expect a quadratic polynomial will do nicely here: let A, B, C be the coefficients so $P(x) = Ax^2 + Bx + C$. Plug in the data,

$$\begin{aligned} P(0) &= C = -2.7 \\ P(2) &= 4A + 2B + C = -4.5 \\ P(1) &= A + B + C = 0.97 \end{aligned} \quad \Rightarrow \quad \left[\begin{array}{ccc|c} A & B & C & \\ \hline 0 & 0 & 1 & -2.7 \\ 4 & 2 & 1 & -4.5 \\ 1 & 1 & 1 & 0.97 \end{array} \right]$$

I put in the A, B, C labels just to emphasize the form of the augmented matrix. We can then perform Gaussian elimination on the matrix (I omit the details) to solve the system,

$$\text{rref} \left[\begin{array}{ccc|c} 0 & 0 & 1 & -2.7 \\ 4 & 2 & 1 & -4.5 \\ 1 & 1 & 1 & 0.97 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & 0 & 0 & -4.52 \\ 0 & 1 & 0 & 8.14 \\ 0 & 0 & 1 & -2.7 \end{array} \right] \quad \Rightarrow \quad \begin{aligned} A &= -4.52 \\ B &= 8.14 \\ C &= -2.7 \end{aligned}$$

The requested polynomial is $\boxed{P(x) = -4.52x^2 + 8.14x - 2.7}$.

Example 1.4.2. Find which cubic polynomial $Q(x)$ have a graph $y = Q(x)$ which fits through the points $(0, -2.7)$, $(2, -4.5)$ and $(1, 0.97)$. Let A, B, C, D be the coefficients of $Q(x) = Ax^3 + Bx^2 + Cx + D$. Plug in the data,

$$\begin{aligned} Q(0) &= D = -2.7 \\ Q(2) &= 8A + 4B + 2C + D = -4.5 \\ Q(1) &= A + B + C + D = 0.97 \end{aligned} \quad \Rightarrow \quad \left[\begin{array}{cccc|c} A & B & C & D & \\ \hline 0 & 0 & 0 & 1 & -2.7 \\ 8 & 4 & 2 & 1 & -4.5 \\ 1 & 1 & 1 & 1 & 0.97 \end{array} \right]$$

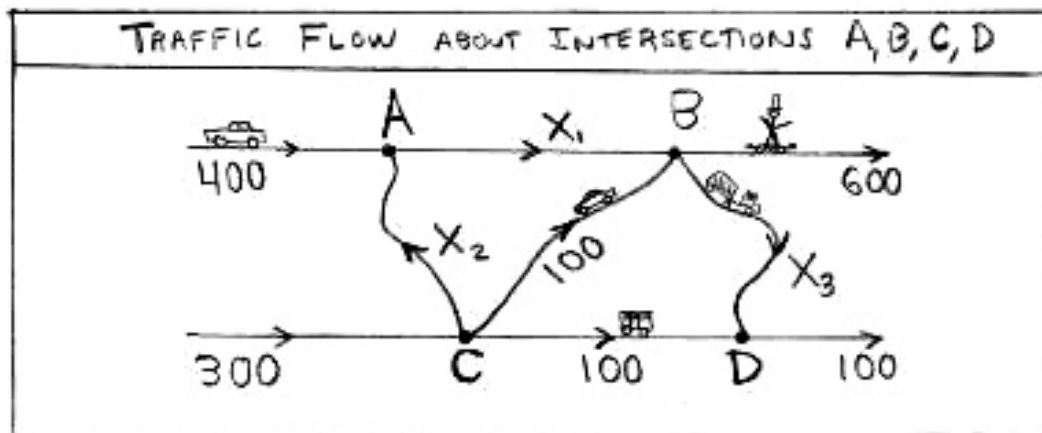
I put in the A, B, C, D labels just to emphasize the form of the augmented matrix. We can then perform Gaussian elimination on the matrix (I omit the details) to solve the system,

$$\text{rref} \left[\begin{array}{cccc|c} 0 & 0 & 0 & 1 & -2.7 \\ 8 & 4 & 2 & 1 & -4.5 \\ 1 & 1 & 1 & 1 & 0.97 \end{array} \right] = \left[\begin{array}{cccc|c} 1 & 0 & -0.5 & 0 & -4.07 \\ 0 & 1 & 1.5 & 0 & 7.69 \\ 0 & 0 & 0 & 1 & -2.7 \end{array} \right] \quad \Rightarrow \quad \begin{aligned} A &= -4.07 + 0.5C \\ B &= 7.69 - 1.5C \\ C &= C \\ D &= -2.7 \end{aligned}$$

It turns out there is a whole family of cubic polynomials which will do nicely. For each $C \in \mathbb{R}$ the polynomial is $\boxed{Q_C(x) = (c - 4.07)x^3 + (7.69 - 1.5C)x^2 + Cx - 2.7}$ fits the given points. We asked a question and found that it had infinitely many answers. Notice the choice $C = 4.07$ gets us back to the last example, in that case $Q_C(x)$ is not really a cubic polynomial.

²...well, modulo that homework I asked you to do, but it's not that hard, even a Sagittarian could do it.

Example 1.4.3. Consider the following traffic-flow pattern. The diagram indicates the flow of cars between the intersections A, B, C, D . Our goal is to analyze the flow and determine the missing pieces of the puzzle, what are the flow-rates x_1, x_2, x_3 . We assume all the given numbers are cars per hour, but we omit the units to reduce clutter in the equations.



We model this by one simple principle: conservation of vehicles

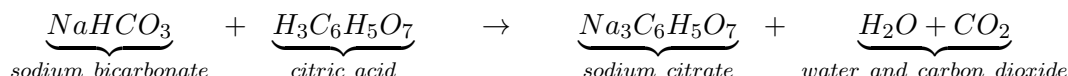
$$\begin{aligned} A: \quad x_1 - x_2 - 400 &= 0 \\ B: \quad -x_1 + 600 - 100 + x_3 &= 0 \\ C: \quad -300 + 100 + 100 + x_2 &= 0 \\ D: \quad -100 + 100 + x_3 &= 0 \end{aligned}$$

This gives us the augmented-coefficient matrix and Gaussian elimination that follows (we have to rearrange the equations to put the constants on the right and the variables on the left before we translate to matrix form)

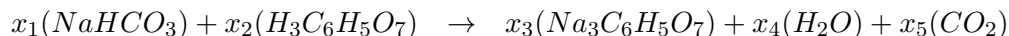
$$\text{rref} \left[\begin{array}{ccc|c} 1 & -1 & 0 & 400 \\ -1 & 0 & 1 & -500 \\ 0 & 1 & 0 & 100 \\ 0 & 0 & 1 & 0 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & 0 & 0 & 500 \\ 0 & 1 & 0 & 100 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right]$$

From this we conclude, $x_3 = 0, x_2 = 100, x_1 = 500$. By the way, this sort of system is called **overdetermined** because we have more equations than unknowns. If such a system is consistent they're often easy to solve. In truth, the rref business is completely unnecessary here. I'm just trying to illustrate what can happen.

Example 1.4.4. (taken from Lay's homework, §1.6#7) Alka Seltzer makes fizzy soothing bubbles through a chemical reaction of the following type:



The reaction above is **unbalanced** because it lacks weights to describe the relative numbers of the various molecules involved in a particular reaction. To **balance** the equation we seek integers x_1, x_2, x_3, x_4, x_5 such that the following reaction is balanced.



In a chemical reaction the atoms that enter the reaction must also leave the reaction. Atoms are neither created nor destroyed in chemical reactions³. It follows that the number of sodium(Na), hydrogen(H), carbon(C) and oxygen(O) atoms must be conserved in the reaction. Each element can be represented by a component in a 4-dimensional vector; (Na, H, C, O). Using this notation the equation to balance the reaction is simply:

$$x_1 \begin{bmatrix} 1 \\ 1 \\ 1 \\ 3 \end{bmatrix} + x_2 \begin{bmatrix} 0 \\ 8 \\ 6 \\ 7 \end{bmatrix} = x_3 \begin{bmatrix} 3 \\ 5 \\ 6 \\ 7 \end{bmatrix} + x_4 \begin{bmatrix} 0 \\ 2 \\ 0 \\ 1 \end{bmatrix} + x_5 \begin{bmatrix} 0 \\ 0 \\ 1 \\ 2 \end{bmatrix}$$

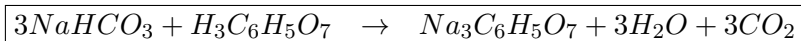
In other words, solve

$$\begin{array}{l} x_1 = 3x_3 \\ x_1 + 8x_2 = 5x_3 + 2x_4 \\ x_1 + 6x_2 = 6x_3 + x_5 \\ 3x_1 + 7x_2 = 6x_3 + x_5 \end{array} \Rightarrow \left[\begin{array}{ccccc|c} 1 & 0 & -3 & 0 & 0 & 0 \\ 1 & 8 & -5 & -2 & 0 & 0 \\ 1 & 6 & -6 & 0 & -1 & 0 \\ 3 & 7 & -6 & 0 & -1 & 0 \end{array} \right]$$

After a few row operations we will deduce,

$$\text{rref} \left[\begin{array}{ccccc|c} 1 & 0 & -3 & 0 & 0 & 0 \\ 1 & 8 & -5 & -2 & 0 & 0 \\ 1 & 6 & -6 & 0 & -1 & 0 \\ 3 & 7 & -6 & 0 & -1 & 0 \end{array} \right] = \left[\begin{array}{ccccc|c} 1 & 0 & 0 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & \frac{-1}{3} & 0 \\ 0 & 0 & 1 & 0 & \frac{-1}{3} & 0 \\ 0 & 0 & 0 & 1 & -1 & 0 \end{array} \right]$$

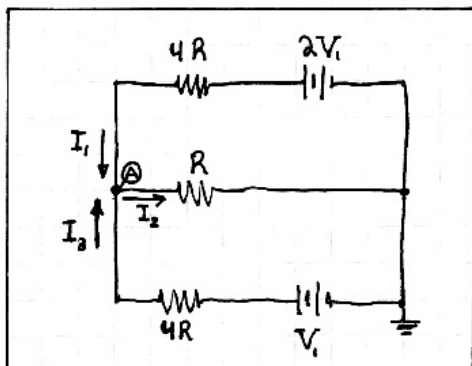
Therefore, $x_1 = x_5, x_2 = x_5/3, x_3 = x_5/3$ and $x_4 = x_5$. Atoms are indivisible (in this context) hence we need to choose $x_5 = 3k$ for $k \in \mathbb{N}$ to assure integer solutions. The basic reaction follows from $x_5 = 3$,



Finding integer solutions to chemical reactions is more easily solved by the method I used as an undergraduate. You guess and check and adjust. Because the solutions are integers it's not too hard to work out. That said, if you don't want to guess then we have a method via Gaussian elimination. Chemists have more to worry about than just this algebra. If you study reactions carefully then there are a host of other considerations involving energy transfer and ultimately quantum mechanics.

³chemistry is based on electronic interactions which do not possess the mechanisms needed for alchemy, transmutation is in fact accomplished in nuclear physics. Ironically, alchemy, while known, is not economical

Example 1.4.5. Let $R = 1\Omega$ and $V_1 = 8V$. Determine the voltage V_A and currents I_1, I_2, I_3 flowing in the circuit as pictured below:



Conservation of charge implies the sum of currents into a node must equal the sum of the currents flowing out of the node. We use Ohm's Law $V = IR$ to set-up the currents, here V should be the voltage dropped across the resistor R .

$$I_1 = \frac{2V_1 - V_A}{4R} \quad \text{Ohm's Law}$$

$$I_2 = \frac{V_A}{R} \quad \text{Ohm's Law}$$

$$I_3 = \frac{V_1 - V_A}{4R} \quad \text{Ohm's Law}$$

$$I_2 = I_1 + I_3 \quad \text{Conservation of Charge at node A}$$

Substitute the first three equations into the fourth to obtain

$$\frac{V_A}{R} = \frac{2V_1 - V_A}{4R} + \frac{V_1 - V_A}{4R}$$

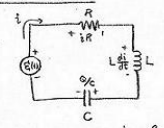
Multiply by $4R$ and we find

$$4V_A = 2V_1 - V_A + V_1 - V_A \Rightarrow 6V_A = 3V_1 \Rightarrow V_A = V_1/2 = 4V.$$

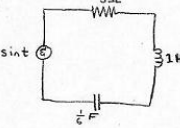
Substituting back into the Ohm's Law equations we determine $I_1 = \frac{16V - 4V}{4\Omega} = 3A$, $I_2 = \frac{4V}{1\Omega} = 4A$ and $I_3 = \frac{8V - 4V}{4\Omega} = 1A$. This obviously checks with $I_2 = I_1 + I_3$. In practice it's not always best to use the full-power of the ref.

Example 1.4.6. (optional material) The following is borrowed from my NCSU calculus II notes. The mathematics to solve 2nd order ODEs is actually really simple, but I just quote it here to illustrate something known as the phasor method in electrical engineering.

RLC : CIRCUITS



Kirchoff's Law's energy is conserved,
 $iR + L \frac{di}{dt} + \frac{Q}{C} = E(t)$
 Where $i = \frac{dQ}{dt}$ the rate of charge passing thru the circuit.
 So we are again faced with a non-homogeneous 2nd order ODE's,
 $L \frac{d^2Q}{dt^2} + R \frac{dQ}{dt} + \frac{1}{C} Q = E(t)$

E4 Find the current for the following circuit if $Q(0) = 0$, $i(0) = 3$,

 $\frac{d^2Q}{dt^2} + 5 \frac{dQ}{dt} + 6Q = \sin(t)$
 $Q(t) = 3.2e^{-2t} - 3.1e^{-3t} + 0.1(\sin t - \cos t)$
 But remember we want $i(t) = \frac{dQ}{dt}$ so differentiate:
 $i(t) = -6.4e^{-2t} + 9.3e^{-3t} + 0.1(\cos t + \sin t)$
 The steady state solⁿ is $i_p = 0.1(\cos t + \sin t)$ (as $t \rightarrow \infty$)

The basic idea is that a circuit with a sinusoidal source can be treated like a DC circuit if we replace the concept of resistance with the "impedance". The basic formulas are

$$Z_{\text{resistor}} = R \quad Z_{\text{inductor}} = j\omega L \quad Z_{\text{capacitor}} = \frac{1}{j\omega C}$$

where $j^2 = -1$ and the complex voltage dropped across Z from a sinusoidal source $\tilde{V} = V_o \exp(j\omega t)$ follows a generalized Ohm's Law of $\tilde{V} = \tilde{I}Z$. The picture circuit has $\omega = 1$ and $R = 5$, $L = 1$ and $C = 1/6$ (omitting units) thus the total impedance of the circuit is

$$Z = R + j\omega L + \frac{1}{j\omega C} = 5 + j - 6j = 5 - 5j$$

Then we can calculate $\tilde{I} = \tilde{V}/Z$,

$$\tilde{I} = \frac{\exp(jt)}{5 - 5j} = \frac{(5 + 5j)\exp(jt)}{(5 + j)(5 - j)} = (0.1 + 0.1j)\exp(jt)$$

Now, this complex formalism actually simultaneously treats a sine and cosine source; $\tilde{V} = \exp(jt) = \cos(t) + j \sin(t)$ the term we are interested in are the imaginary components: notice that

$$\tilde{I} = (0.1 + 0.1j)e^{jt} = (0.1 + 0.1j)(\cos(t) + j \sin(t)) = 0.1[\cos(t) - \sin(t)] + 0.1j[\cos(t) + \sin(t)]$$

implies $\text{Im}(\tilde{I}) = 0.1[\cos(t) + \sin(t)]$. We find the steady-state solution $I_p(t) = 0.1[\cos(t) + \sin(t)]$ (this is the solution for large times, there are two other terms in the solution are called transient). The phasor method has replaced differential equations argument with a bit of complex arithmetic. If we had a circuit with several loops and various inductors, capacitors and resistors we could use the complex Ohm's Law and conservation of charge to solve the system in the same way we solved the previous example. If you like this sort of thing you're probably an ECE major.

1.5 conclusions

We concluded the last section with a rather believable (but tedious to prove) Theorem. We do the same here,

Theorem 1.5.1.

Given a system of m linear equations and n unknowns the solution set falls into one of the following cases:

1. the solution set is empty.
2. the solution set has only one element.
3. the solution set is infinite.

Proof: Consider the augmented coefficient matrix $[A|b] \in \mathbb{R}^{m \times (n+1)}$ for the system (Theorem 1.2.11 assures us it exists and is unique). Calculate $rref[A|b]$. If $rref[A|b]$ contains a row of zeros with a 1 in the last column then the system is inconsistent and we find no solutions thus the solution set is empty.

Suppose $rref[A|b]$ does not contain a row of zeros with a 1 in the far right position. Then there are less than $n + 1$ pivot columns. Suppose there are n pivot columns, let c_i for $i = 1, 2, \dots, m$ be the entries in the rightmost column. We find $x_1 = c_1, x_2 = c_2, \dots, x_n = c_m$. Consequently the solution set is $\{(c_1, c_2, \dots, c_m)\}$.

If $rref[A|b]$ has $k < n$ pivot columns then there are $(n + 1 - k)$ -non-pivot positions. Since the last column corresponds to b it follows there are $(n - k)$ free variables. But, $k < n$ implies $0 < n - k$ hence there is at least one free variable. Therefore there are infinitely many solutions. \square

Theorem 1.5.2.

Suppose that $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{m \times p}$ then the first n columns of $rref[A]$ and $rref[A|B]$ are identical.

Proof: The forward pass of the elimination proceeds from the leftmost-column to the rightmost-column. The matrices A and $[A|B]$ have the same n -leftmost columns thus the n -leftmost columns are identical after the forward pass is complete. The backwards pass acts on column at a time just clearing out above the pivots. Since the $rref(A)$ and $rref[A|B]$ have identical n -leftmost columns the backwards pass modifies those columns in the same way. Thus the n -leftmost columns of A and $[A|B]$ will be identical. \square

The proofs in the Appendix of the text may appeal to you more if you are pickier on these points.

Theorem 1.5.3.

Given n -linear equations in n -unknowns $Ax = b$, a unique solution x exists iff $\text{rref}[A|b] = [I|x]$. Moreover, if $\text{rref}[A] \neq I$ then there is no unique solution to the system of equations.

Proof: If a unique solution $x_1 = c_1, x_2 = c_2, \dots, x_n = c_n$ exists for a given system of equations $Ax = b$ then we know

$$A_{i1}c_1 + A_{i2}c_2 + \dots + A_{in}c_n = b_i$$

for each $i = 1, 2, \dots, n$ and this is the only ordered set of constants which provides such a solution. Suppose that $\text{rref}[A|b] \neq [I|c]$. If $\text{rref}[A|b] = [I|d]$ and $d \neq c$ then d is a new solution thus the solution is not unique, this contradicts the given assumption. Consider, on the other hand, the case $\text{rref}[A|b] = [J|f]$ where $J \neq I$. If there is a row where f is nonzero and yet J is zero then the system is inconsistent. Otherwise, there are infinitely many solutions since J has at least one non-pivot column as $J \neq I$. Again, we find contradictions in every case except the claimed result. It follows if $x = c$ is the unique solution then $\text{rref}[A|b] = [I|c]$. The converse follows essentially the same argument, if $\text{rref}[A|b] = [I|c]$ then clearly $Ax = b$ has solution $x = c$ and if that solution were not unique then we be able to find a different rref for $[A|b]$ but that contradicts the uniqueness of rref. \square

There is much more to say about the meaning of particular patterns in the reduced row echelon form of the matrix. We will continue to mull over these matters in later portions of the course. Theorem 1.5.1 provides us the big picture. Again, I find it remarkable that two equations and two unknowns already revealed these patterns.

Remark 1.5.4.

Incidentally, you might notice that the Gauss-Jordan algorithm did not assume all the structure of the real numbers. For example, we never needed to use the ordering relations $<$ or $>$. All we needed was addition, subtraction and the ability to multiply by the inverse of a nonzero number. Any **field** of numbers will likewise work. Theorems 1.5.1 and 1.2.11 also hold for matrices of rational (\mathbb{Q}) or complex (\mathbb{C}) numbers. We will encounter problems which require calculation in \mathbb{C} . If you are interested in encryption then calculations over a finite field \mathbb{Z}_p are necessary. In contrast, Gaussssian elimination does not work for matrices of integers since we do not have fractions to work with in that context. Some such questions are dealt with in Abstract Algebra I and II.

Chapter 2

vectors

The first section in this chapter is intended to introduce the reader to the concept of geometric vectors. I show that both vector addition and scalar multiplication naturally flow from intuitive geometry. Then we abstract those concepts in the second section to give concrete definitions of vector addition and scalar multiplication in \mathbb{R}^n . Matrices are again introduced and further notation is used to elucidate calculations performed in the previous chapter. Finally linear transformations on vectors are defined and used to illustrate a number of geometric concepts.

2.1 geometric preliminaries

The concept of a vector is almost implicit with the advent of Cartesian geometry. Rene Descartes' great contribution was the realization that geometry had an algebraic description if we make an identification of points in the plane with pairs of real numbers. This identification is so ubiquitous it is hard to imagine the plane without imagining pairs of numbers. Euclid had no idea of x or y coordinates, instead just lines, circles and constructive axioms. Analytic geometry is the study of geometry as formulated by Descartes. Because numbers are identified with points we are able to state equations expressing relations between points. For example, if $h, k, R \in \mathbb{R}$ then the set of all points $(x, y) \in \mathbb{R}^2$ which satisfy

$$(x - h)^2 + (y - k)^2 = R^2$$

is a circle of radius R centered at (h, k) . We can analyze the circle by studying the algebra of the equation above. In calculus we even saw how implicit differentiation reveals the behaviour of the tangent lines to the circle.

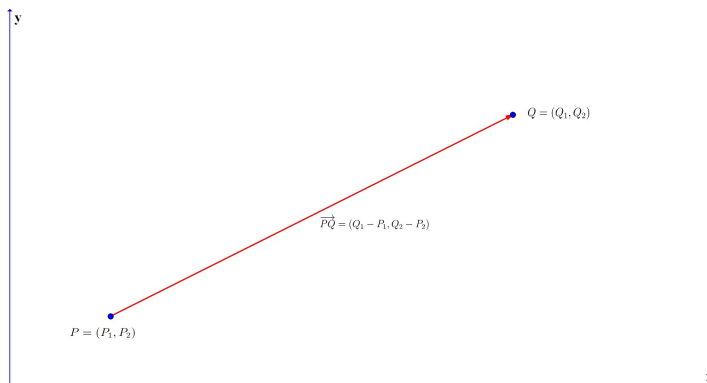
Very well, what about the points themselves ? What relations if any do arbitrary points in the plane admit? For one, you probably already know about how to get directed line segments from points. A common notation in highschool geometry¹ is that the line from point $P = (Q_1, Q_2)$ to

¹a dying subject apparently

another point $Q = (Q_1, Q_2)$ is \overrightarrow{PQ} where we define:

$$\overrightarrow{PQ} = Q - P = (Q_1 - P_1, Q_2 - P_2).$$

A directed line-segment is also called a **vector**².



Consider a second line segment going from Q to $R = (R_1, R_2)$ this gives us the directed line segment of $\overrightarrow{QR} = R - Q = (R_1 - Q_1, R_2 - Q_2)$. What then about the directed line segment from the original point P to the final point R ? How is $\overrightarrow{PR} = R - P = (R_1 - P_1, R_2 - P_2)$ related to \overrightarrow{PQ} and \overrightarrow{QR} ? Suppose we define addition of points in the same way we defined the subtraction of points:

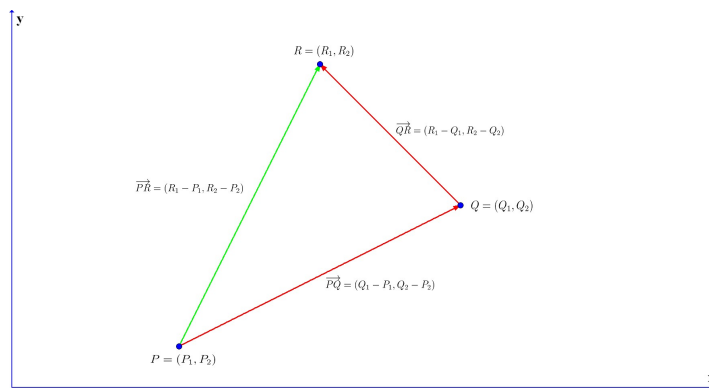
$$(V_1, V_2) + (W_1, W_2) = (V_1 + W_1, V_2 + W_2).$$

Will this definition be consistent with the geometrically suggested result $\overrightarrow{PQ} + \overrightarrow{QR} = \overrightarrow{PR}$? Consider,

$$\begin{aligned} \overrightarrow{PQ} + \overrightarrow{QR} &= (Q_1 - P_1, Q_2 - P_2) + (R_1 - Q_1, R_2 - Q_2) \\ &= (Q_1 - P_1 + R_1 - Q_1, Q_2 - P_2 + R_2 - Q_2) \\ &= (R_1 - P_1, R_2 - P_2) \\ &= \overrightarrow{PR}. \end{aligned}$$

We find the addition and subtraction of directed line segments is consistent with the usual tip-tail addition of vectors in the plane.

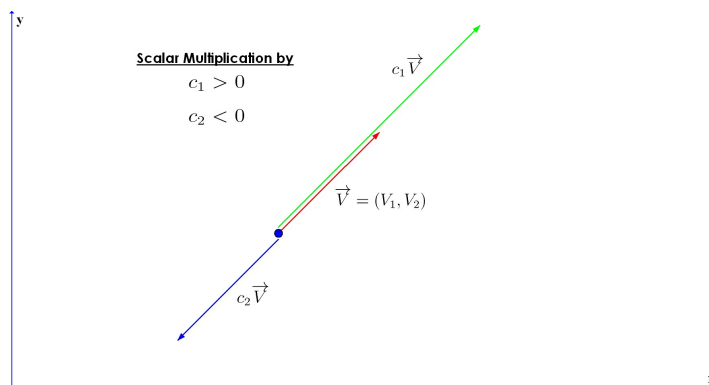
²however, not every vector in this course is a directed line segment.



What else can we do ? It seems natural to assume that $\overrightarrow{PQ} + \overrightarrow{PQ} = 2\overrightarrow{PQ}$ but what does multiplication by a number mean for a vector? What definition should we propose? Note if $\overrightarrow{PQ} = (Q_1 - P_1, Q_2 - P_2)$ then $\overrightarrow{PQ} + \overrightarrow{PQ} = 2\overrightarrow{PQ}$ implies $2(\overrightarrow{PQ}) = (2(Q_1 - P_1), 2(Q_2 - P_2))$. Therefore, we define for $c \in \mathbb{R}$,

$$c(V_1, V_2) = (cV_1, cV_2).$$

This definition is naturally consistent with the definition we made for addition. We can understand multiplication of a vector by a number as an operation which **scales** the vector. In other words, multiplying a vector by a number will change the length of the vector. Multiplication of a vector by a number is often called **scalar multiplication**. Scalars are numbers.



Vectors based at the origin are naturally identified with points: the directed line segment from $Q = (0, 0)$ to P is naturally identified with the point P .

$$\overrightarrow{QP} = (P_1, P_2) - (0, 0) = (P_1, P_2).$$

In other words we can identify the point $P = (P_1, P_2)$ with the directed line segment from the origin $\vec{P} = (P_1, P_2)$. Unless context suggests otherwise vectors in this course are assumed to be based at the origin.

2.2 n -dimensional space

Two dimensional space is $\mathbb{R}^2 = \mathbb{R} \times \mathbb{R}$. To obtain n -dimensional space we just take the Cartesian product of n -copies of \mathbb{R} .

Definition 2.2.1.

Let $n \in \mathbb{N}$, we define $\mathbb{R}^n = \{(x_1, x_2, \dots, x_n) \mid x_j \in \mathbb{R} \text{ for } j = 1, 2, \dots, n\}$. If $v \in \mathbb{R}^n$ then we say v is an **n-vector**. The numbers in the vector are called the **components**; $v = (v_1, v_2, \dots, v_n)$ has j -th component v_j .

Notice, a consequence of the definition above and the construction of the Cartesian product³ is that two vectors v and w are equal iff $v_j = w_j$ for all j . Equality of two vectors is only true if all components are found to match. Addition and scalar multiplication are naturally generalized from the $n = 2$ case.

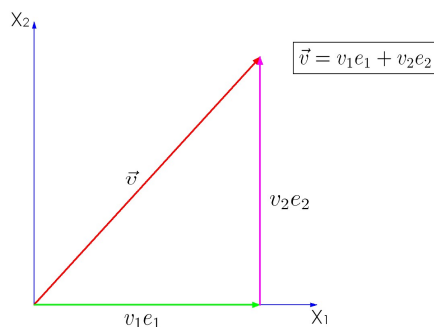
Definition 2.2.2.

Define functions $+: \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}^n$ and $\cdot: \mathbb{R} \times \mathbb{R}^n \rightarrow \mathbb{R}^n$ by the following rules: for each $v, w \in \mathbb{R}^n$ and $c \in \mathbb{R}$:

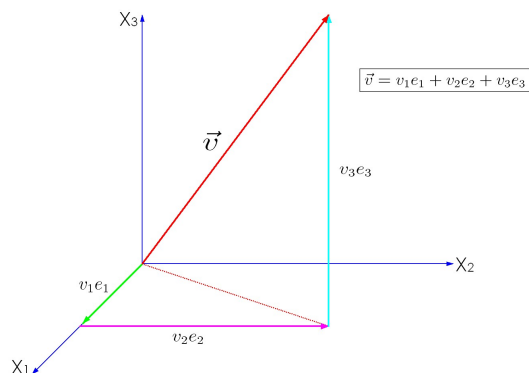
$$(1.) (v + w)_j = v_j + w_j \qquad (2.) (cv)_j = cv_j$$

for all $j \in \{1, 2, \dots, n\}$. The operation $+$ is called **vector addition** and it takes two vectors $v, w \in \mathbb{R}^n$ and produces another vector $v + w \in \mathbb{R}^n$. The operation \cdot is called **scalar multiplication** and it takes a number $c \in \mathbb{R}$ and a vector $v \in \mathbb{R}^n$ and produces another vector $c \cdot v \in \mathbb{R}^n$. Often we simply denote $c \cdot v$ by juxtaposition cv .

If you are a gifted at visualization then perhaps you can add three-dimensional vectors in your mind. If you're mind is really unhinged maybe you can even add 4 or 5 dimensional vectors. The beauty of the definition above is that we have no need of pictures. Instead, algebra will do just fine. That said, let's draw a few pictures.



³see my Math 200 notes or ask me if interested, it's not entirely trivial



Notice these pictures go to show how you can break-down vectors into component vectors which point in the direction of the coordinate axis. Vectors of length⁴ one which point in the coordinate directions make up what is called the **standard basis**⁵. It is convenient to define special notation for the standard basis. First I define a useful shorthand,

Definition 2.2.3.

The symbol $\delta_{ij} = \begin{cases} 1 & , i = j \\ 0 & , i \neq j \end{cases}$ is called the **Kronecker delta**.

For example, $\delta_{22} = 1$ while $\delta_{12} = 0$.

Definition 2.2.4.

Let $e_i \in \mathbb{R}^{n \times 1}$ be defined by $(e_i)_j = \delta_{ij}$. The size of the vector e_i is determined by context. We call e_i the i -th standard basis vector.

Example 2.2.5. Let me expand on what I mean by "context" in the definition above:

In \mathbb{R} we have $e_1 = (1) = 1$ (by convention we drop the brackets in this case)

In \mathbb{R}^2 we have $e_1 = (1, 0)$ and $e_2 = (0, 1)$.

In \mathbb{R}^3 we have $e_1 = (1, 0, 0)$ and $e_2 = (0, 1, 0)$ and $e_3 = (0, 0, 1)$.

In \mathbb{R}^4 we have $e_1 = (1, 0, 0, 0)$ and $e_2 = (0, 1, 0, 0)$ and $e_3 = (0, 0, 1, 0)$ and $e_4 = (0, 0, 0, 1)$.

Example 2.2.6. Any vector in \mathbb{R}^n can be written as a sum of these basic vectors. For example,

$$\begin{aligned} v = (1, 2, 3) &= (1, 0, 0) + (0, 2, 0) + (0, 0, 3) \\ &= 1(1, 0, 0) + 2(0, 1, 0) + 3(0, 0, 1) \\ &= e_1 + 2e_2 + 3e_3. \end{aligned}$$

We say that v is a **linear combination** of e_1, e_2 and e_3 .

⁴the length of vectors is an important concept which we mine in depth later in the course

⁵for now we use the term "basis" without meaning, in Chapter 5 we make a great effort to refine the concept.

The concept of a linear combination is very important.

Definition 2.2.7.

A **linear combination** of objects A_1, A_2, \dots, A_k is a sum

$$c_1 A_1 + c_2 A_2 + \dots + c_k A_k = \sum_{i=1}^k c_i A_i$$

where $c_i \in \mathbb{R}$ for each i .

We will look at linear combinations of vectors, matrices and even functions in this course. If $c_i \in \mathbb{C}$ then we call it a *complex linear combination*. The proposition below generalizes the calculation from Example 2.2.6.

Proposition 2.2.8.

Every vector in \mathbb{R}^n is a linear combination of e_1, e_2, \dots, e_n .

Proof: Let $v = (v_1, v_2, \dots, v_n) \in \mathbb{R}^n$. By the definition of vector addition:

$$\begin{aligned} v &= (v_1, v_2, \dots, v_n) \\ &= (v_1, 0, \dots, 0) + (0, v_2, \dots, v_n) \\ &= (v_1, 0, \dots, 0) + (0, v_2, \dots, 0) + \dots + (0, 0, \dots, v_n) \\ &= (v_1, 0 \cdot v_1, \dots, 0 \cdot v_1) + (0 \cdot v_2, v_2, \dots, 0 \cdot v_2) + \dots + (0 \cdot v_n, 0 \cdot v_n, \dots, v_n) \end{aligned}$$

In the last step I rewrote each zero to emphasize that the each entry of the k -th summand has a v_k factor. Continue by applying the definition of scalar multiplication to each vector in the sum above we find,

$$\begin{aligned} v &= v_1(1, 0, \dots, 0) + v_2(0, 1, \dots, 0) + \dots + v_n(0, 0, \dots, 1) \\ &= v_1 e_1 + v_2 e_2 + \dots + v_n e_n. \end{aligned}$$

Therefore, every vector in \mathbb{R}^n is a linear combination of e_1, e_2, \dots, e_n . For each $v \in \mathbb{R}^n$ we have $v = \sum_{i=1}^n v_i e_i$. \square

Proposition 2.2.9. *the vector properties of \mathbb{R}^n .*

Suppose $n \in \mathbb{N}$. For all $x, y, z \in \mathbb{R}^n$ and $a, b \in \mathbb{R}$,

1. (P1) $x + y = y + x$ for all $x, y \in \mathbb{R}^n$,
2. (P2) $(x + y) + z = x + (y + z)$ for all $x, y, z \in \mathbb{R}^n$,
3. (P3) there exists $0 \in \mathbb{R}^n$ such that $x + 0 = x$ for all $x \in \mathbb{R}^n$,
4. (P4) for each $x \in \mathbb{R}^n$ there exists $-x \in \mathbb{R}^n$ such that $x + (-x) = 0$,
5. (P5) $1 \cdot x = x$ for all $x \in \mathbb{R}^n$,
6. (P6) $(ab) \cdot x = a \cdot (b \cdot x)$ for all $x \in \mathbb{R}^n$ and $a, b \in \mathbb{R}$,
7. (P7) $a \cdot (x + y) = a \cdot x + a \cdot y$ for all $x, y \in \mathbb{R}^n$ and $a \in \mathbb{R}$,
8. (P8) $(a + b) \cdot x = a \cdot x + b \cdot x$ for all $x \in \mathbb{R}^n$ and $a, b \in \mathbb{R}$,
9. (P9) If $x, y \in \mathbb{R}^n$ then $x + y$ is a single element in \mathbb{R}^n , (we say \mathbb{R}^n is closed with respect to addition)
10. (P10) If $x \in \mathbb{R}^n$ and $c \in \mathbb{R}$ then $c \cdot x$ is a single element in \mathbb{R}^n . (we say \mathbb{R}^n is closed with respect to scalar multiplication)

We call 0 in P3 the **zero vector** and the vector $-x$ is called the **additive inverse** of x . We will usually omit the \cdot and instead denote scalar multiplication by juxtaposition; $a \cdot x = ax$.

Proof: all the properties follow immediately from the definitions of addition and scalar multiplication in \mathbb{R}^n as well as properties of real numbers. Consider,

$$(x + y)_j = x_j + y_j = \underbrace{y_j + x_j}_{\star} = (y + x)_j$$

where \star follows because real number addition commutes. Since the calculation above holds for each $j = 1, 2, \dots, n$ it follows that $x + y = y + x$ for all $x, y \in \mathbb{R}^n$ hence P1 is true. Very similarly P2 follows from associativity of real number addition. To prove P3 simply define, as usual, $0_j = 0$; The zero vector is the vector with all zero components. Note

$$(x + 0)_j = x_j + 0_j = x_j + 0 = x_j$$

which holds for all $j = 1, 2, \dots, n$ hence $x + 0 = x$ for all $x \in \mathbb{R}^n$. I leave the remainder of the properties for the reader. \square

The preceding proposition will be mirrored in an abstract context later in the course. So, it is important. On the other hand, we will prove it again in the next chapter in the context of a subcase of the matrix algebra. I include it here to complete the logic of this chapter.

2.2.1 concerning notation for vectors

Definition 2.2.10. *points are viewed as column vectors in this course.*

In principle one can use column vectors for everything or row vectors for everything. I choose a subtle notation that allows us to use both. On the one hand it is nice to write vectors as rows since the typesetting is easier. However, once you start talking about matrix multiplication then it is natural to write the vector to the right of the matrix and we will soon see that the vector should be written as a column vector for that to be reasonable. Therefore, we adopt the following **convention**

$$(v_1, v_2, \dots, v_n) = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix}.$$

If I want to denote a real row vector then we will just write $[v_1, v_2, \dots, v_n]$.

The convention above is by no means universal. Various linear algebra books deal with this notational dilemma and number of different ways. In the first version of my linear algebra notes I used $\mathbb{R}^{n \times 1}$ everywhere just to be relentlessly explicit that we were using column vectors for \mathbb{R}^n . The set of all $n \times 1$ matrices is the set of all column vectors which I denote by $\mathbb{R}^{n \times 1}$ whereas the set of all $1 \times n$ matrices is the set of all row vectors which we denote by $\mathbb{R}^{1 \times n}$. We discuss these matters in general in next chapter. The following example is merely included to expand on the notation.

Example 2.2.11. *Suppose $x + y + z = 3$, $x + y = 2$ and $x - y - z = -1$. This system can be written as a single vector equation by simply stacking these equations into a column vector:*

$$\begin{bmatrix} x + y + z \\ x + y \\ x - y - z \end{bmatrix} = \begin{bmatrix} 3 \\ 2 \\ -1 \end{bmatrix}$$

Furthermore, we can break up the vector of variables into linear combination where the coefficients in the sum are the variables x, y, z :

$$x \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} + y \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix} + z \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} = \begin{bmatrix} 3 \\ 2 \\ -1 \end{bmatrix}$$

Note that the solution to the system is $x = 1, y = 1, z = 1$.

2.3 linear combinations and spanning

We saw that linear combinations of the standard basis will generate any vector in \mathbb{R}^n in the previous section. We now set out to answer a set similar question:

PROBLEM: Given vectors v_1, v_2, \dots, v_k and a vector b do there exist constants c_1, c_2, \dots, c_k such that $c_1v_1 + c_2v_2 + \dots + c_kv_k = b$? If so, how should we determine them in general?

We have all the tools we need to solve such problems. I'll show a few examples before I state the general algorithm.

Example 2.3.1. Problem: given that $v = (2, -1, 3)$, $w = (1, 1, 1)$ and $b = (4, 1, 5)$ find values for x, y such that $xv + yw = b$ (if possible).

Solution: using our column notation we find $xv + yw = b$ gives

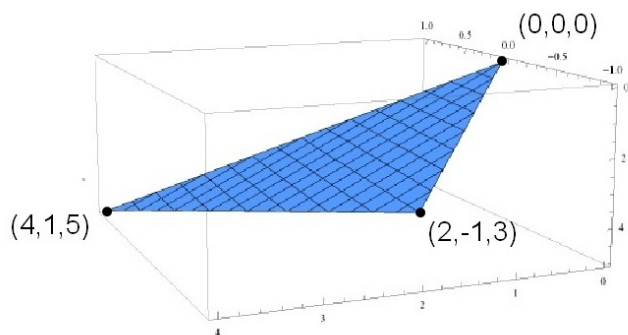
$$x \begin{bmatrix} 2 \\ -1 \\ 3 \end{bmatrix} + y \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ 1 \\ 5 \end{bmatrix} \Rightarrow \begin{bmatrix} 2x + y \\ -x + y \\ 3x + y \end{bmatrix} = \begin{bmatrix} 4 \\ 1 \\ 5 \end{bmatrix}$$

We are faced with solving the system of equations $2x + y = 4$, $-x + y = 1$ and $3x + y = 5$. As we discussed in depth last chapter we can efficiently solve this type of problem in general by Gaussian elimination on the corresponding augmented coefficient matrix. In this problem, you can calculate that

$$\text{rref} \left[\begin{array}{cc|c} 2 & 1 & 4 \\ -1 & 1 & 1 \\ 3 & 1 & 5 \end{array} \right] = \left[\begin{array}{cc|c} 1 & 0 & 1 \\ 0 & 1 & 2 \\ 0 & 0 & 0 \end{array} \right]$$

hence $x = 1$ and $y = 2$. Indeed, it is easy to check that $v + 2w = b$.

The geometric question which is equivalent to the previous question is as follows: "is the vector b found in the plane which contains v and w "? Here's a picture of the calculation we just performed:



The set of all linear combinations of several vectors in \mathbb{R}^n is called the *span* of those vectors. To be precise

Definition 2.3.2.

Let $S = \{v_1, v_2, \dots, v_k\} \subset \mathbb{R}^n$ be a finite set of n -vectors then $\text{span}(S)$ is defined to be the set of all linear combinations formed from vectors in S :

$$\text{span}\{v_1, v_2, \dots, v_k\} = \left\{ \sum_{i=1}^k c_i v_i \mid c_i \in \mathbb{R} \text{ for } i = 1, 2, \dots, k \right\}$$

If $W = \text{span}(S)$ then we say that S is a **generating set** for W .

If we have one vector then it has a span which could be a line. With two vectors we might generate a plane. With three vectors we might generate a volume. With four vectors we might generate a hypervolume or 4-volume. We'll return to these geometric musings in § 2.5 and explain why I have used the word "might" rather than an affirmative "will" in these claims. For now, we return to the question of how to decide if a given vector is in the span of another set of vectors.

Example 2.3.3. Problem: Let $b_1 = (1, 1, 0)$, $b_2 = (0, 1, 1)$ and $b_3 = (0, 1, -1)$. Is⁶ $e_3 \in \text{span}\{b_1, b_2, b_3\}$?

Solution: Find the explicit linear combination of b_1, b_2, b_3 that produces e_3 . We seek to find $x, y, z \in \mathbb{R}$ such that $xb_1 + yb_2 + zb_3 = e_3$,

$$x \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} + y \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} + z \begin{bmatrix} 0 \\ 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \Rightarrow \begin{bmatrix} x \\ x + y + z \\ y - z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

Following essentially the same arguments as the last example we find this question of solving the system formed by gluing the given vectors into a matrix and doing row reduction. In particular, we can solve the vector equation above by solving the corresponding system below:

$$\left[\begin{array}{ccc|c} 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 \\ 0 & 1 & -1 & 1 \end{array} \right] \xrightarrow{r_2 - r_1 \rightarrow r_2} \left[\begin{array}{ccc|c} 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & -1 & 1 \end{array} \right] \xrightarrow{r_3 - r_2 \rightarrow r_3} \left[\begin{array}{ccc|c} 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & -2 & 1 \end{array} \right] \xrightarrow{\begin{array}{l} -r_3/2 \rightarrow r_3 \\ r_2 - r_3 \rightarrow r_2 \\ r_1 - r_3 \rightarrow r_1 \end{array}} \left[\begin{array}{ccc|c} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1/2 \\ 0 & 0 & 1 & -1/2 \end{array} \right]$$

Therefore, $x = 0, y = \frac{1}{2}$ and $z = -\frac{1}{2}$. We find that $e_3 = \frac{1}{2}b_1 + \frac{1}{2}b_2 - \frac{1}{2}b_3$ thus $e_3 \in \text{span}\{b_1, b_2, b_3\}$.

⁶challenge: once you understand this example for e_3 try answering it for other vectors or for an arbitrary vector $v = (v_1, v_2, v_3)$. How would you calculate $x, y, z \in \mathbb{R}$ such that $v = xb_1 + yb_2 + zb_3$?

The power of the matrix technique shines bright in the next example. Sure you could guess the last two, but as things get messy we'll want a refined efficient algorithm to dispatch spanning questions with ease.

Example 2.3.4. Problem: Let $b_1 = (1, 2, 3, 4)$, $b_2 = (0, 1, 0, 1)$ and $b_3 = (0, 0, 1, 1)$. Is $w = (1, 1, 4, 4) \in \text{span}\{b_1, b_2, b_3\}$?

Solution: Following the same method as the last example we seek to find x_1, x_2 and x_3 such that $x_1 b_1 + x_2 b_2 + x_3 b_3 = w$ by solving the aug. coeff. matrix as is our custom:

$$\begin{aligned}
 [b_1|b_2|b_3|w] &= \left[\begin{array}{ccc|c} 1 & 0 & 0 & 1 \\ 2 & 1 & 0 & 1 \\ 3 & 0 & 1 & 4 \\ 4 & 1 & 1 & 4 \end{array} \right] \xrightarrow{\substack{r_2 - 2r_1 \rightarrow r_2 \\ r_3 - 3r_1 \rightarrow r_3 \\ r_4 - 4r_1 \rightarrow r_4}} \left[\begin{array}{ccc|c} 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & -1 \\ 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 0 \end{array} \right] \xrightarrow{r_4 - r_2 \rightarrow r_4} \\
 &\left[\begin{array}{ccc|c} 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & -1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 1 \end{array} \right] \xrightarrow{r_4 - r_3 \rightarrow r_4} \left[\begin{array}{ccc|c} 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & -1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{array} \right] = \text{rref}[b_1|b_2|b_3|w]
 \end{aligned}$$

We find $x_1 = 1, x_2 = -1, x_3 = 1$ thus $\boxed{w = b_1 - b_2 + b_3}$. Therefore, $w \in \text{span}\{b_1, b_2, b_3\}$.

Pragmatically, if the question is sufficiently simple you may not need to use the augmented coefficient matrix to solve the question. I use them here to illustrate the method.

Example 2.3.5. Problem: Let $b_1 = (1, 1, 0)$ and $b_2 = (0, 1, 1)$. Is $e_2 \in \text{span}\{b_1, b_2\}$?

Solution: Attempt to find the explicit linear combination of b_1, b_2 that produces e_2 . We seek to find $x, y \in \mathbb{R}$ such that $xb_1 + yb_2 = e_3$,

$$x \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} + y \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} x \\ x+y \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

We don't really need to consult the augmented matrix to solve this problem. Clearly $x = 0$ and $y = 0$ is found from the first and third components of the vector equation above. But, the second component yields $x + y = 1$ thus $0 + 0 = 1$. It follows that this system is inconsistent and we may conclude that $w \notin \text{span}\{b_1, b_2\}$. For the sake of curiosity let's see how the augmented solution matrix looks in this case: omitting details of the row reduction,

$$\text{rref} \left[\begin{array}{cc|c} 1 & 0 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{array} \right] = \left[\begin{array}{cc|c} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{array} \right]$$

note the last row again confirms that this is an inconsistent system.

Proposition 2.3.6.

Given vectors $v_1, v_2, \dots, v_k \in \mathbb{R}^n$ and another vector $b \in \mathbb{R}^n$ we can solve the vector equation $x_1v_1 + x_2v_2 + \dots + x_kv_k = b$ by Gaussian elimination of the corresponding matrix problem $[v_1|v_2|\dots|v_k|b]$. Moreover, $b \in \text{span}\{v_1, v_2, \dots, v_k\}$ iff $[v_1|v_2|\dots|v_k|b]$ represents the augmented matrix of a consistent system of equations.

Proof: note that solving the single vector equation $x_1v_1 + x_2v_2 + \dots + x_kv_k = b$ for x_1, x_2, \dots, x_k is equivalent to solving n -scalar equations

$$\begin{aligned} x_1(v_1)_1 + x_2(v_2)_1 + \dots + x_k(v_k)_1 &= b_1 \\ x_1(v_1)_2 + x_2(v_2)_2 + \dots + x_k(v_k)_2 &= b_2 \\ \vdots \quad \quad \quad \vdots \quad \quad \quad \vdots \quad \quad \quad \vdots & \\ x_1(v_1)_n + x_2(v_2)_n + \dots + x_k(v_k)_n &= b_n. \end{aligned}$$

But, this can be solved by performing Gaussian elimination on the matrix

$$\left[\begin{array}{cccc|c} (v_1)_1 & (v_2)_1 & \cdots & (v_k)_1 & b_1 \\ (v_1)_2 & (v_2)_2 & \cdots & (v_k)_2 & b_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ (v_1)_n & (v_2)_n & \cdots & (v_k)_n & b_n \end{array} \right].$$

Therefore, $b \in \text{span}\{v_1, v_2, \dots, v_k\}$ iff the system above reduces to a consistent system. \square

2.4 multiplication of matrix by a vector

Definition 2.4.1.

Let $A = [A_1|A_2|\cdots|A_k]$ be a matrix with n -rows and k -columns which is formed by concatenating k column vectors $A_1, A_2, \dots, A_k \in \mathbb{R}^n$. Also, let $x = (x_1, x_2, \dots, x_k) \in \mathbb{R}^k$. The product of A and x is denoted Ax and is defined by the weighted vector sum of the columns A_l of the matrix A by the components x_k of x . In particular,

$$Ax = x_1A_1 + x_2A_2 + \cdots + x_kA_k$$

Example 2.4.2. Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ and $v = \begin{bmatrix} x \\ y \end{bmatrix}$ then we may calculate the product Av as follows:

$$Av = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = x \begin{bmatrix} 1 \\ 3 \end{bmatrix} + y \begin{bmatrix} 2 \\ 4 \end{bmatrix} = \begin{bmatrix} x + 2y \\ 3x + 4y \end{bmatrix}.$$

Notice that the product of an $n \times k$ matrix with a $k \times 1$ vector yields another vector of size $k \times 1$. In the example above we observed the pattern $(2 \times 2)(2 \times 1) \rightarrow (2 \times 1)$.

Example 2.4.3. Let $A = \begin{bmatrix} 1 & 1 & 1 \\ a & b & c \end{bmatrix}$ and $v = \begin{bmatrix} x \\ y \\ z \end{bmatrix}$ then we may calculate the product Av as follows:

$$Av = \begin{bmatrix} 1 & 1 & 1 \\ a & b & c \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = x \begin{bmatrix} 1 \\ a \end{bmatrix} + y \begin{bmatrix} 1 \\ b \end{bmatrix} + z \begin{bmatrix} 1 \\ c \end{bmatrix} = \begin{bmatrix} x + y + z \\ ax + by + cz \end{bmatrix}.$$

Proposition 2.4.4.

If $A = [A_1|A_2|\cdots|A_k] \in \mathbb{R}^{n \times k}$ and $b \in \mathbb{R}^n$ then the matrix equation $Ax = b$ has the same solution set $x = (x_1, x_2, \dots, x_k)$ as the vector equation

$$x_1A_1 + x_2A_2 + \cdots + x_kA_k = b$$

and the matrix system

$$[A_1|A_2|\cdots|A_k|b].$$

The proof of this Proposition hinges on the definition of matrix multiplication as given in Definition 2.4.1 and Proposition 2.3.6. I leave the details to the reader. It is convenient at this point to introduce further notation to describe a matrix since we may not always wish to think of the matrix in terms of its columns.

Definition 2.4.5.

Let x_1, x_2, \dots, x_k be k variables and suppose $b_i, A_{ij} \in \mathbb{R}$ for $1 \leq i \leq n$ and $1 \leq j \leq k$. The system of linear equations

$$A_{11}x_1 + A_{12}x_2 + \cdots + A_{1k}x_k = b_1$$

$$A_{21}x_1 + A_{22}x_2 + \cdots + A_{2k}x_k = b_2$$

$$\vdots \quad \vdots \quad \vdots \quad \vdots$$

$$A_{n1}x_1 + A_{n2}x_2 + \cdots + A_{nk}x_k = b_n$$

has **coefficient matrix** A , the **inhomogeneous term** b and **augmented coefficient matrix** $[A|b]$ defined below:

$$A = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1k} \\ A_{21} & A_{22} & \cdots & A_{2k} \\ \vdots & \vdots & \cdots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nk} \end{bmatrix}, \quad b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}, \quad [A|b] = \left[\begin{array}{cccc|c} A_{11} & A_{12} & \cdots & A_{1k} & b_1 \\ A_{21} & A_{22} & \cdots & A_{2k} & b_2 \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nk} & b_n \end{array} \right].$$

A vector $x \in \mathbb{R}^k$ for which $Ax = b$ is called a **vector solution** to the matrix form of the system.

Naturally, solutions x_1, x_2, \dots, x_k to the original system are in 1-1 correspondance with the vector solutions of the corresponding matrix form of the equation. Moreover, we know Gaussian elimination on the augmented coefficient matrix is a reliable algorithm to solve any such system.

Definition 2.4.6.

Let $Ax = b$ be a system of n equations and k -unknowns then x is in the solution set of the system. In particular, we denote the solution set by $Sol_{[A|b]}$ where

$$Sol_{[A|b]} = \{x \in \mathbb{R}^k \mid Ax = b\}$$

We learned in the last chapter that the solution set either contained a single point, an infinite number of points or no points at all. Sorry if this all seems a little redundant. We will think in terms of matrix notation for the remainder of the course. I sometimes forget to distinguish between the system of equations and their matrix form. The difference at first seems to just be notation, but you'll see the notation seems to have a life of its own. We now revisit two examples from the previous chapter to write the results in matrix notation.

Example 2.4.7. We found that the system in Example 1.3.1,

$$x + 2y - 3z = 1$$

$$2x + 4y = 7$$

$$-x + 3y + 2z = 0$$

has the unique solution $x = 83/30, y = 11/30$ and $z = 5/6$. This means the matrix equation $Av = b$ where

$$Av = \underbrace{\begin{bmatrix} 1 & 2 & -3 \\ 2 & 4 & 0 \\ -1 & 3 & 2 \end{bmatrix}}_A \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}}_v = \underbrace{\begin{bmatrix} 1 \\ 7 \\ 0 \end{bmatrix}}_b \quad \text{has vector solution} \quad v = \begin{bmatrix} 83/30 \\ 11/30 \\ 5/6 \end{bmatrix}.$$

Example 2.4.8. We can rewrite the following system of linear equations

$$\begin{aligned} x_1 + x_4 &= 0 \\ 2x_1 + 2x_2 + x_5 &= 0 \\ 4x_1 + 4x_2 + 4x_3 &= 1 \end{aligned}$$

in matrix form this system of equations is $Av = b$ where

$$Av = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 2 & 2 & 0 & 0 & 1 \\ 4 & 4 & 4 & 0 & 0 \end{bmatrix}}_A \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}}_v = \underbrace{\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}}_b.$$

Gaussian elimination on the augmented coefficient matrix reveals (see Example 1.2.7 for details of the Gaussian elimination)

$$\text{rref} \left[\begin{array}{ccccc|c} 1 & 0 & 0 & 1 & 0 & 0 \\ 2 & 2 & 0 & 0 & 1 & 0 \\ 4 & 4 & 4 & 0 & 0 & 1 \end{array} \right] = \left[\begin{array}{ccccc|c} 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & -1 & 1/2 & 0 \\ 0 & 0 & 1 & 0 & -1/2 & 1/4 \end{array} \right].$$

Consequently, x_4, x_5 are free and solutions are of the form

$$\begin{aligned} x_1 &= -x_4 \\ x_2 &= x_4 - \frac{1}{2}x_5 \\ x_3 &= \frac{1}{4} + \frac{1}{2}x_5 \end{aligned}$$

for all $x_4, x_5 \in \mathbb{R}$. The vector form of the solution is as follows:

$$v = \begin{bmatrix} -x_4 \\ x_4 - \frac{1}{2}x_5 \\ \frac{1}{4} + \frac{1}{2}x_5 \\ x_4 \\ x_5 \end{bmatrix} = x_4 \begin{bmatrix} -1 \\ 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} + x_5 \begin{bmatrix} 0 \\ -\frac{1}{2} \\ \frac{1}{2} \\ 0 \\ 1 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \frac{1}{4} \\ 0 \\ 0 \end{bmatrix}.$$

Remark 2.4.9.

You might ask the question: what is the geometry of the solution set above ? Let $S = \text{Sol}_{[A|b]} \subset \mathbb{R}^5$, we see S is formed by tracing out all possible linear combinations of the vectors $v_1 = (-1, 1, 0, 1, 0)$ and $v_2 = (0, -\frac{1}{2}, \frac{1}{2}, 0, 1)$ based from the point $p_o = (0, 0, \frac{1}{4}, 0, 0)$. In other words, this is a two-dimensional plane containing the vectors v_1, v_2 and the point p_o . This plane is placed in a 5-dimensional space, this means that at any point on the plane you could go in three different directions away from the plane.

The definition we gave for matrix multiplication is not how I usually multiply. Instead I think in terms of what are called **dot-products**. The dot-product of two n -vectors is easy to compute:

$$(a_1, a_2, \dots, a_n) \cdot (b_1, b_2, \dots, b_n) = a_1b_1 + a_2b_2 + \dots + a_nb_n.$$

Proposition 2.4.10.

Suppose $A = [A_{ij}] \in \mathbb{R}^{k \times n}$ and $v = [v_j] \in \mathbb{R}^n$. Let R_j denote the j -th row of A converted to a column vector; $R_j = (A_{j1}, A_{j2}, \dots, A_{jn})$ for $j = 1, 2, \dots, k$. The product of Av can be calculated by computing k dot-products as follows:

$$Av = \begin{bmatrix} R_1 \cdot v \\ R_2 \cdot v \\ \vdots \\ R_k \cdot v \end{bmatrix}$$

Proof: we begin with the definition of matrix multiplication, consider the j -th component of the vector equation $Av = v_1 \text{col}_1(A) + v_2 \text{col}_2(A) + \dots + v_n \text{col}_n(A)$,

$$(Av)_j = v_1(\text{col}_1(A))_j + v_2(\text{col}_2(A))_j + \dots + v_n(\text{col}_n(A))_j$$

But, observe that $((\text{col}_1(A))_j, (\text{col}_2(A))_j, \dots, (\text{col}_n(A))_j) = (A_{j1}, A_{j2}, \dots, A_{jn}) = R_j$ hence the j -th component of Av is precisely $v \cdot R_j$ as claimed. \square

The following corollary follows easily from the proof above.

Corollary 2.4.11.

If $A = [A_{ij}] \in \mathbb{R}^{k \times n}$ and $v = [v_j] \in \mathbb{R}^n$ then $(Av)_i = \sum_{j=1}^n A_{ij}v_j$ for each $i = 1, 2, \dots, k$.

Example 2.4.12. Consider the following generic system of two equations and three unknowns,

$$\begin{aligned} ax + by + cz &= d \\ ex + fy + gz &= h \end{aligned}$$

in matrix form this system of equations is $Av = b$ where

$$Av = \underbrace{\begin{bmatrix} a & b & c \\ e & f & g \end{bmatrix}}_A \underbrace{\begin{bmatrix} x \\ y \\ z \end{bmatrix}}_v = \begin{bmatrix} (a, b, c) \cdot (x, y, z) \\ (e, f, g) \cdot (x, y, z) \end{bmatrix} = \begin{bmatrix} ax + by + cz \\ ex + fy + gz \end{bmatrix} = \underbrace{\begin{bmatrix} d \\ h \end{bmatrix}}_b$$

I find it easier to think in dot-products.

Example 2.4.13. Let $A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$ and $v = \begin{bmatrix} 1 \\ 0 \\ -3 \end{bmatrix}$ calculate Av .

$$Av = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ -3 \end{bmatrix} = \begin{bmatrix} (1, 2, 3) \cdot (1, 0, -3) \\ (4, 5, 6) \cdot (1, 0, -3) \\ (7, 8, 9) \cdot (1, 0, -3) \end{bmatrix} = \begin{bmatrix} -2 \\ -14 \\ -20 \end{bmatrix}.$$

Proposition 2.4.14.

Let $A \in \mathbb{R}^{n \times m}$ and $x, y \in \mathbb{R}^m$ and $c \in \mathbb{R}$

1. $A(x + y) = Ax + Ay$
2. $A(cx) = cAx$

Proof: I'll use Corollary 2.4.11 to frame the proof. Let $A = [A_{ij}] \in \mathbb{R}^{n \times m}$, $x = [x_j] \in \mathbb{R}^m$ and $y = [y_j] \in \mathbb{R}^m$. Observe that

$$(A(x + y))_i = \underbrace{\sum_{j=1}^m A_{ij}(x + y)_j}_{\text{def. vector add.}} = \underbrace{\sum_{j=1}^m A_{ij}(x_j + y_j)}_{\text{prop. of finite sums}} = \underbrace{\sum_{j=1}^m A_{ij}x_j + \sum_{j=1}^m A_{ij}y_j}_{\text{prop. of finite sums}} = (Ax)_i + (Ay)_i$$

holds for all $i = 1, 2, \dots, n$. Therefore, $A(x + y) = Ax + Ay$. Likewise observe that,

$$(A(cx))_i = \underbrace{\sum_{j=1}^m A_{ij}(cx)_j}_{\text{using def. of scalar mult. and then finite sums}} = \sum_{j=1}^m A_{ij}cx_j = c \left(\sum_{j=1}^m A_{ij}x_j \right) = c(Ax)_i = (cAx)_i$$

holds for all $i = 1, 2, \dots, n$. Therefore, $A(cx) = cAx$. \square

It's doubtful anyone ever showed you how to prove properties of finite sums. I include a brief appendix to explain if you are curious. In a nutshell, finite sums are defined inductively so you have to use proof by mathematical induction to rigorously establish their various properties.

Let's pause to think about what we've learned about spans in this section. First of all the very definition of matrix multiplication defined Av to be a linear combination of the columns of A so clearly $Av = b$ has a solution iff b is a linear combination of the columns in A .

We have seen for a particular matrix A and a given vector b it may or may not be the case that $Av = b$ has a solution. It turns out that certain special matrices will have a solution for each choice of b . The theorem below is taken from Lay's text on page 43. The abbreviation **TFAE** means "The Following Are Equivalent".

Theorem 2.4.15.

Suppose $A = [A_{ij}] \in \mathbb{R}^{k \times n}$ then TFAE,

1. $Av = b$ has a solution for each $b \in \mathbb{R}^k$
2. each $b \in \mathbb{R}^k$ is a linear combination of the columns of A
3. columns of A span \mathbb{R}^k
4. A has a pivot position in each row.

Proof: the equivalence of (1.) and (2.) is immediate from the definition of matrix multiplication of a matrix and a vector. Item (3.) says that the set of all linear combinations of the columns of A is equal to \mathbb{R}^k , thus (2.) \Leftrightarrow (3.). Finally, item (4.) is not just notation.

Suppose (4.) is true. Recall that $rref[A]$ and $rref[A|b]$ have matching columns up to the rightmost column of $rref[A|b]$ by the Theorem 1.5.2. It follows that $rref[A|b]$ is a consistent system since we cannot have a row where the first nonzero entry occurs in the last column. But, this result is independent of b hence we have a solution of $Av = b$ for each possible $b \in \mathbb{R}^k$. Hence (4.) \Rightarrow (1.).

Conversely suppose (1.) is true; suppose $Av = b$ has a solution for each $b \in \mathbb{R}^k$. If $rref[A]$ has a row of zeros then we could choose $b \neq 0$ with a nonzero component in that row and the equation $Av = b$ would be inconsistent. But that contradicts (1.) hence it must be the case that $rref[A]$ has no row of zeros hence every row must be a pivot row. We have (1.) \Rightarrow (4.).

In conclusion, (1.) \Leftrightarrow (2.) \Leftrightarrow (3.) and (1.) \Leftrightarrow (4.) hence (4.) \Leftrightarrow (1.) \Leftrightarrow (2.) \Leftrightarrow (3.) \square .

In truth this theorem really only scratches the surface. We can say more if the matrix A is square. But, I leave the fun for a later chapter. This much fun for now should suffice.

2.5 linear independence

In the previous sections we have only considered questions based on a fixed spanning set. We asked if $b \in \text{span}\{v_1, v_2, \dots, v_n\}$ and we even asked if it was possible for all b . What we haven't thought about yet is the following:

PROBLEM: Given vectors v_1, v_2, \dots, v_k and a vector $b = c_1v_1 + c_2v_2 + \dots + c_kv_k$ for some constants c_j is it possible that b can be written as a linear combination of some subset of $\{v_1, v_2, \dots, v_k\}$? If so, how should we determine which vectors can be taken away from the spanning set? How should we decide which vectors to keep and which are redundant?

The concept of linear independence is central to answering these questions. We will examine the basics of linear independence in this section. However, I should mention that this is a story which cannot told in it's entirety until we develop a few more tools⁷.

Definition 2.5.1.

If a vector v_k can be written as a linear combination of vectors $\{v_1, v_2, \dots, v_{k-1}\}$ then we say that the vectors $\{v_1, v_2, \dots, v_{k-1}, v_k\}$ are **linearly dependent**.
If the vectors $\{v_1, v_2, \dots, v_{k-1}, v_k\}$ are not linear dependent then they are said to be **linearly independent**.

Example 2.5.2. Let $v = [1 \ 2 \ 3]^T$ and $w = [2 \ 4 \ 6]^T$. Clearly v, w are linearly dependent since $w = 2v$.

I often quote the following proposition as the definition of linear independence, it is an equivalent statement and as such can be used as the definition (but not by us, I already made the definition above). If this was our definition then our definition would become a proposition. Math always has a certain amount of this sort of ambiguity.

Proposition 2.5.3.

Let $v_1, v_2, \dots, v_k \in \mathbb{R}^n$. The set of vectors $\{v_1, v_2, \dots, v_k\}$ is linearly independent iff

$$c_1v_1 + c_2v_2 + \dots + c_kv_k = 0 \Rightarrow c_1 = c_2 = \dots = c_k = 0.$$

Proof: (\Rightarrow) Suppose $\{v_1, v_2, \dots, v_k\}$ is linearly independent. Assume that there exist constants c_1, c_2, \dots, c_k such that

$$c_1v_1 + c_2v_2 + \dots + c_kv_k = 0$$

and at least one constant, say c_j , is nonzero. Then we can divide by c_j to obtain

$$\frac{c_1}{c_j}v_1 + \frac{c_2}{c_j}v_2 + \dots + v_j + \dots + \frac{c_k}{c_j}v_k = 0$$

⁷we must wait for the CCP; but, we are the ones we've been waiting for so it will not be too long a wait. Only Jorge will understand this.

solve for v_j , (we mean for $\widehat{v_j}$ to denote the deletion of v_j from the list)

$$v_j = -\frac{c_1}{c_j}v_1 - \frac{c_2}{c_j}v_2 - \cdots - \widehat{v_j} - \cdots - \frac{c_k}{c_j}v_k$$

but this means that v_j linearly depends on the other vectors hence $\{v_1, v_2, \dots, v_k\}$ is linearly dependent. This is a contradiction, therefore $c_j = 0$. Note j was arbitrary so we may conclude $c_j = 0$ for all j . Therefore, $c_1v_1 + c_2v_2 + \cdots + c_kv_k = 0 \Rightarrow c_1 = c_2 = \cdots = c_k = 0$.

Proof: (\Leftarrow) Assume that

$$c_1v_1 + c_2v_2 + \cdots + c_kv_k = 0 \Rightarrow c_1 = c_2 = \cdots = c_k = 0.$$

If $v_j = b_1v_1 + b_2v_2 + \cdots + \widehat{b_jv_j} + \cdots + b_kv_k$ then $b_1v_1 + b_2v_2 + \cdots + b_jv_j + \cdots + b_kv_k = 0$ where $b_j = -1$, this is a contradiction. Therefore, for each j , v_j is not a linear combination of the other vectors. Consequently, $\{v_1, v_2, \dots, v_k\}$ is linearly independent.

Proposition 2.5.4.

If S is a finite set of vectors which contains the zero vector then S is linearly dependent.

Proof: Let $\{\vec{0}, v_2, \dots, v_k\} = S$ and observe that

$$1\vec{0} + 0v_2 + \cdots + 0v_k = 0$$

Thus $c_1\vec{0} + c_2v_2 + \cdots + c_kv_k = 0$ does not imply $c_1 = 0$ hence the set of vectors is not linearly independent. Thus S is linearly dependent. \square

Proposition 2.5.5.

Let v and w be nonzero vectors.

$$v, w \text{ are linearly dependent} \Leftrightarrow \exists k \neq 0 \in \mathbb{R} \text{ such that } v = kw.$$

Proof: Suppose v, w are linearly dependent then there exist constants c_1, c_2 , not all zero, such that $c_1v + c_2w = 0$. Suppose that $c_1 = 0$ then $c_2w = 0$ hence⁸ $c_2 = 0$ or $w = 0$. But, this is a contradiction since v, w are nonzero and at least one of c_1, c_2 must be nonzero. Therefore, $c_1 \neq 0$. Likewise, if $c_2 = 0$ we find a similar contradiction. Hence c_1, c_2 are both nonzero and we calculate $v = (-c_2/c_1)w$, identify that $k = -c_2/c_1$. \square

⁸if the product of a scalar and a vector in \mathbb{R}^n is zero then you can prove that one or both is zero by examining the components of the vector equation

Remark 2.5.6.

For two vectors the term "linearly dependent" can be taken quite literally: two vectors are linearly dependent if they point along the same line. For three vectors they are linearly dependent if they point along the same line or possibly lay in the same plane. When we get to four vectors we can say they are linearly dependent if they reside in the same volume, plane or line. I don't find the geometric method terribly successful for dimensions higher than two. However, it is neat to think about the geometric meaning of certain calculations in dimensions higher than 3. We can't even draw it but we can elucidate all sorts of information with the mathematics of linear algebra.

Example 2.5.7. Let $v = [1 \ 2 \ 3]^T$ and $w = [1 \ 0 \ 0]^T$. Let's prove these are linearly independent. Assume that $c_1v + c_2w = 0$, this yields

$$c_1 \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} + c_2 \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

thus $c_1 + c_2 = 0$ and $2c_1 = 0$ and $3c_1 = 0$. We find $c_1 = c_2 = 0$ thus v, w are linearly independent. Alternatively, you could explain why there does not exist any $k \in \mathbb{R}$ such that $v = kw$

Think about this, if the set of vectors $\{v_1, v_2, \dots, v_k\} \subset \mathbb{R}^n$ is linearly independent then the equation $c_1v_1 + c_2v_2 + \dots + c_kv_k = 0$ has the unique solution $c_1 = 0, c_2 = 0, \dots, c_k = 0$. Notice we can reformulate the problem as a matrix equation:

$$c_1v_1 + c_2v_2 + \dots + c_kv_k = 0 \Leftrightarrow [v_1|v_2|\dots|v_k][c_1 \ c_2 \ \dots \ c_k]^T = 0$$

The matrix $[v_1|v_2|\dots|v_k]$ is an $n \times k$. This is great. We can use the matrix techniques we already developed to probe for linear independence of a set of vectors.

Proposition 2.5.8.

Let $\{v_1, v_2, \dots, v_k\}$ be a set of vectors in \mathbb{R}^n .

1. If $\text{rref}[v_1|v_2|\dots|v_k]$ has less than k pivot columns then the set of vectors $\{v_1, v_2, \dots, v_k\}$ is linearly dependent.
2. If $\text{rref}[v_1|v_2|\dots|v_k]$ has k pivot columns then the set of vectors $\{v_1, v_2, \dots, v_k\}$ is linearly independent.

Proof: Denote $V = [v_1|v_2|\dots|v_k]$ and $c = [c_1, c_2, \dots, c_k]^T$. If V contains a linearly independent set of vectors then we must find that $Vc = 0$ implies $c = 0$. Consider $Vc = 0$, this is equivalent to using Gaussian elimination on the augmented coefficient matrix $[V|0]$. We know this system is consistent since $c = 0$ is a solution. Thus Theorem 1.5.1 tells us that there is either a unique solution or infinitely many solutions.

Clearly if the solution is unique then $c = 0$ is the only solution and hence the implication $Av = 0$ implies $c = 0$ holds true and we find the vectors are linearly independent. In this case we would find

$$\text{rref}[v_1|v_2|\cdots|v_k] = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 1 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix} = \begin{bmatrix} I_k \\ 0 \end{bmatrix}$$

where there are n -rows in the matrix above. If $n = k$ then there would be no zeros below the k -th row.

If there are infinitely many solutions then there will be free variables in the solution of $Vc = 0$. If we set the free variables to 1 we then find that $Vc = 0$ does not imply $c = 0$ since at least the free variables are nonzero. Thus the vectors are linearly dependent in this case, proving (2.). Rather than attempting to sketch a general $\text{rref}[V|0]$ I will illustrate with several examples to follow. \square

Before I get to the examples let me glean one more fairly obvious statement from the proof above:

Corollary 2.5.9.

If $\{v_1, v_2, \dots, v_k\}$ is a set of vectors in \mathbb{R}^n and $k > n$ then the vectors are linearly dependent.

Proof: Proposition 2.5.8 tells us that the set is linearly independent if there are k pivot columns in $[v_1|\cdots|v_k]$. However, that is impossible since $k > n$ this means that there will be at least one column of zeros in $\text{rref}[v_1|\cdots|v_k]$. Therefore the vectors are linearly dependent. \square

This Proposition is obvious but useful. We may have at most 2 linearly independent vectors in \mathbb{R}^2 , 3 in \mathbb{R}^3 , 4 in \mathbb{R}^4 , and so forth...

Example 2.5.10. Determine if v_1, v_2, v_3 (given below) are linearly independent or dependent. If the vectors are linearly dependent show how they depend on each other.

$$v_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \quad v_2 = \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} \quad v_3 = \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix}$$

We seek to use the Proposition 2.5.8. Consider then,

$$[v_1|v_2|v_3] = \begin{bmatrix} 1 & 2 & 3 \\ 1 & 1 & 2 \\ 1 & 0 & 1 \end{bmatrix} \xrightarrow[r_3 - r_1 \rightarrow r_3]{r_2 - r_1 \rightarrow r_2} \begin{bmatrix} 1 & 2 & 3 \\ 0 & -1 & -1 \\ 0 & -2 & -2 \end{bmatrix} \xrightarrow[r_3 - 2r_2 \rightarrow r_3]{r_1 + 2r_2 \rightarrow r_2} \begin{bmatrix} 1 & 0 & 1 \\ 0 & -1 & -1 \\ 0 & 0 & 0 \end{bmatrix}$$

Thus we find that,

$$\text{rref}[v_1|v_2|v_3] = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

hence the variable c_3 is free in the solution of $Vc = 0$. We find solutions of the form $c_1 = -c_3$ and $c_2 = -c_3$. This means that

$$-c_3v_1 - c_3v_2 + c_3v_3 = 0$$

for any value of c_3 . I suggest $c_3 = 1$ is easy to plug in,

$$-v_1 - v_2 + v_3 = 0 \quad \text{or we could write} \quad v_3 = v_1 + v_2$$

We see clearly that v_3 is a linear combination of v_1, v_2 .

Example 2.5.11. Determine if v_1, v_2, v_3, v_4 (given below) are linearly independent or dependent.

$$v_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad v_2 = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix} \quad v_3 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \end{bmatrix} \quad v_4 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

We seek to use the Proposition 2.5.8. Omitting details we find,

$$\text{rref}[v_1|v_2|v_3|v_4] = \text{rref} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

In this case no variables are free, the only solution is $c_1 = 0, c_2 = 0, c_3 = 0, c_4 = 0$ hence the set of vectors $\{v_1, v_2, v_3, v_4\}$ is linearly independent.

Example 2.5.12. Determine if v_1, v_2, v_3 (given below) are linearly independent or dependent. If the vectors are linearly dependent show how they depend on each other.

$$v_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 3 \end{bmatrix} \quad v_2 = \begin{bmatrix} 3 \\ 1 \\ 2 \\ 0 \end{bmatrix} \quad v_3 = \begin{bmatrix} 2 \\ 1 \\ 2 \\ -3 \end{bmatrix}$$

We seek to use the Proposition 2.5.8. Consider $[v_1|v_2|v_3] =$

$$\begin{bmatrix} 1 & 3 & 2 \\ 0 & 1 & 1 \\ 0 & 2 & 2 \\ 3 & 0 & -3 \end{bmatrix} \xrightarrow[r_4 - 3r_1 \rightarrow r_4]{} \begin{bmatrix} 1 & 3 & 2 \\ 0 & 1 & 1 \\ 0 & 2 & 2 \\ 0 & -9 & -9 \end{bmatrix} \xrightarrow[r_4 + 9r_2 \rightarrow r_4]{\begin{matrix} r_1 - 3r_2 \rightarrow r_1 \\ r_3 - 2r_2 \rightarrow r_3 \end{matrix}} \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} = \text{rref}[V].$$

Hence the variable c_3 is free in the solution of $Vc = 0$. We find solutions of the form $c_1 = c_3$ and $c_2 = -c_3$. This means that

$$c_3v_1 - c_3v_2 + c_3v_3 = 0$$

for any value of c_3 . I suggest $c_3 = 1$ is easy to plug in,

$$v_1 - v_2 + v_3 = 0 \quad \text{or we could write} \quad v_3 = v_2 - v_1$$

We see clearly that v_3 is a linear combination of v_1, v_2 .

Example 2.5.13. Determine if v_1, v_2, v_3, v_4 (given below) are linearly independent or dependent. If the vectors are linearly dependent show how they depend on each other.

$$v_1 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} \quad v_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \quad v_3 = \begin{bmatrix} 0 \\ 1 \\ 1 \\ 0 \end{bmatrix} \quad v_4 = \begin{bmatrix} 0 \\ 1 \\ 2 \\ 0 \end{bmatrix}$$

We seek to use the Proposition 2.5.8. Consider $[v_1|v_2|v_3|v_4] =$

$$\begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 \\ 1 & 1 & 2 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \xrightarrow{r_1 \leftrightarrow r_3} \begin{bmatrix} 1 & 1 & 2 & 0 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \xrightarrow{r_1 - r_2 \rightarrow r_1} \begin{bmatrix} 1 & 0 & 1 & -1 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} = \text{rref}[v_1|v_2|v_3|v_4].$$

Hence the variables c_3 and c_4 are free in the solution of $Vc = 0$. We find solutions of the form $c_1 = -c_3 + c_4$ and $c_2 = -c_3 - c_4$. This means that

$$(c_4 - c_3)v_1 - (c_3 + c_4)v_2 + c_3v_3 + c_4v_4 = 0$$

for any value of c_3 or c_4 . I suggest $c_3 = 1, c_4 = 0$ is easy to plug in,

$$-v_1 - v_2 + v_3 = 0 \quad \text{or we could write} \quad v_3 = v_2 + v_1$$

Likewise select $c_3 = 0, c_4 = 1$ to find

$$v_1 - v_2 + v_4 = 0 \quad \text{or we could write} \quad v_4 = v_2 - v_1$$

We find that v_3 and v_4 are linear combinations of v_1 and v_2 .

2.6 introduction to linear transformations and mapping

Let me briefly review what you should already know from Math 200/250 about functions in the abstract: Recall that a function $f : A \rightarrow B$ is a single-valued assignment of elements in A to elements in B . We say that $\text{dom}(f) = A$ and $\text{codomain}(f) = B$. Furthermore, recall that the range of the function is the set of all outputs: $\text{range}(f) = f(A)$. If $f(A) = B$ then we say that f is a **surjection** or equivalently f is **onto**. If $f(x) = f(y)$ implies $x = y$ for all $x, y \in A$ then we say that f is **injective** or equivalently f is **1-1**. In this section we will have occasion to use these terms as they apply to functions from \mathbb{R}^n to \mathbb{R}^m .

A function from $U \subset \mathbb{R}^n$ to $V \subseteq \mathbb{R}^k$ is called a **mapping**. You should have studied mappings in calculus II whether you realized it or not. Coordinate transformations of the plane are mappings from $\mathbb{R}^2 \rightarrow \mathbb{R}^2$.

Example 2.6.1. Let $F(r, \theta) = (r \cos(\theta), r \sin(\theta))$ for $(r, \theta) \in [0, \infty) \times [0, 2\pi]$. This mapping takes lines in the polar plane and maps them to either circles or rays in the Cartesian plane. This is an interesting mapping, but our focus is on transformations which take lines in the domain and map them to lines in the range.

In fact, mappings are much more general than linear transformations (we study mappings in advanced calculus). We may also say that a linear transformation is a **linear mapping**.

Definition 2.6.2.

Let $V = \mathbb{R}^n, W = \mathbb{R}^k$. If a mapping $L : V \rightarrow W$ satisfies

1. $L(x + y) = L(x) + L(y)$ for all $x, y \in V$; this is called **additivity**.
2. $L(cx) = cL(x)$ for all $x \in V$ and $c \in \mathbb{R}$; this is called **homogeneity**.

then we say L is a linear transformation. If $n = m$ then we may say that L is a linear transformation on \mathbb{R}^n .

Example 2.6.3. Let $L(x, y) = (x, 2y)$. This is a mapping from \mathbb{R}^2 to \mathbb{R}^2 . Notice

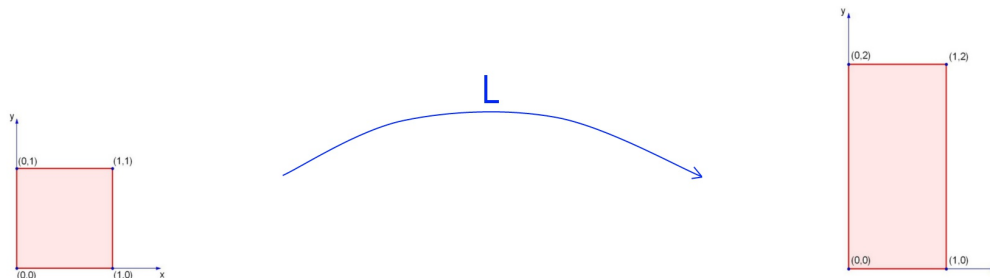
$$L((x, y) + (z, w)) = L(x + z, y + w) = (x + z, 2(y + w)) = (x, 2y) + (z, 2w) = L(x, y) + L(z, w)$$

and

$$L(c(x, y)) = L(cx, cy) = (cx, 2(cy)) = c(x, 2y) = cL(x, y)$$

for all $(x, y), (z, w) \in \mathbb{R}^2$ and $c \in \mathbb{R}$. Therefore, L is a linear transformation on \mathbb{R}^2 . Let's examine how this function maps the unit square in the domain: suppose $(x, y) \in [0, 1] \times [0, 1]$. This means $0 \leq x \leq 1$ and $0 \leq y \leq 1$. Label the Cartesian coordinates of the range by u, v so $L(x, y) = (x, 2y) = (u, v)$. We have $x = u$ thus $0 \leq u \leq 1$. Also, $v = 2y$ hence $y = \frac{v}{2}$ hence $0 \leq y \leq 1$ implies $0 \leq \frac{v}{2} \leq 1$ or $0 \leq v \leq 2$.

To summarize: $L([0, 1] \times [0, 1]) = [0, 1] \times [0, 2]$. This mapping has stretched out the horizontal direction.



The method of analysis we used in the preceding example was a little clumsy, but for general mappings that is more or less the method of attack. You pick some shapes or curves in the domain and see what happens under the mapping. For linear mappings there is an easier way. It turns out that if we map some shape with straight sides then the image will likewise be a shape with flat sides (or faces in higher dimensions). Therefore, to find the image we need only map the corners of the shape then connect the dots. However, I should qualify that it may not be the case the type of shape is preserved. We could have a rectangle in the domain get squished into a line or point in the domain. We would like to understand when such squishing will happen and also when a given mapping will actually cover the whole codomain. For linear mappings there are very satisfying answers to these questions in terms of the theory we have already discussed in this chapter.

Proposition 2.6.4.

If $A \in \mathbb{R}^{m \times n}$ and $L : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is defined by $L(x) = Ax$ for each $x \in \mathbb{R}^n$ then L is a linear transformation.

Proof: Let $A \in \mathbb{R}^{m \times n}$ and define $L : \mathbb{R}^n \rightarrow \mathbb{R}^m$ by $L(x) = Ax$ for each $x \in \mathbb{R}^n$. Let $x, y \in \mathbb{R}^n$ and $c \in \mathbb{R}$,

$$L(x + y) = A(x + y) = Ax + Ay = L(x) + L(y)$$

and

$$L(cx) = A(cx) = cAx = cL(x)$$

thus L is a linear transformation. \square

Obviously this gives us a nice way to construct examples. The following proposition is really at the heart of all the geometry in this section.

Proposition 2.6.5.

Let $\mathcal{L} = \{p + tv \mid t \in [0, 1], p, v \in \mathbb{R}^n \text{ with } v \neq 0\}$ define a line segment from p to $p + v$ in \mathbb{R}^n . If $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a linear transformation then $T(\mathcal{L})$ is either a line-segment from $T(p)$ to $T(p + v)$ or a point.

Proof: suppose T and \mathcal{L} are as in the proposition. Let $y \in T(\mathcal{L})$ then by definition there exists $x \in \mathcal{L}$ such that $T(x) = y$. But this implies there exists $t \in [0, 1]$ such that $x = p + tv$ so $T(p + tv) = y$. Notice that

$$y = T(p + tv) = T(p) + T(tv) = T(p) + tT(v).$$

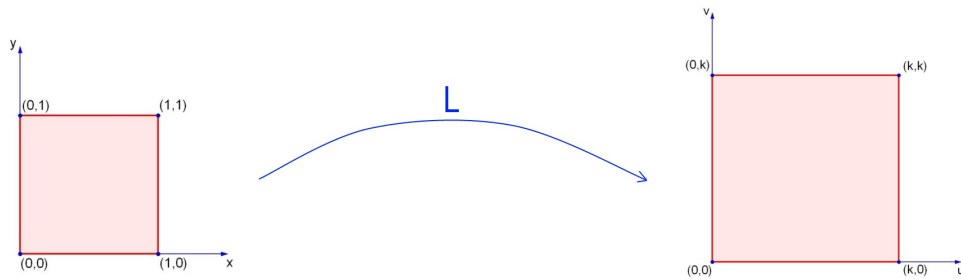
which implies $y \in \{T(p) + sT(v) \mid s \in [0, 1]\} = \mathcal{L}_2$. Therefore, $T(\mathcal{L}) \subseteq \mathcal{L}_2$. Conversely, suppose $z \in \mathcal{L}_2$ then $z = T(p) + sT(v)$ for some $s \in [0, 1]$ but this yields by linearity of T that $z = T(p + sv)$ hence $z \in T(\mathcal{L})$. Since we have that $T(\mathcal{L}) \subseteq \mathcal{L}_2$ and $\mathcal{L}_2 \subseteq T(\mathcal{L})$ it follows that $T(\mathcal{L}) = \mathcal{L}_2$. Note that \mathcal{L}_2 is a line-segment provided that $T(v) \neq 0$, however if $T(v) = 0$ then $\mathcal{L}_2 = \{T(p)\}$ and the proposition follows. \square

My choice of mapping the unit square has no particular significance in the examples below. I merely wanted to keep it simple and draw your eye to the distinction between the examples. In each example we'll map the four corners of the square to see where the transformation takes the unit-square. Those corners are simply $(0, 0), (1, 0), (1, 1), (0, 1)$ as we traverse the square in a counter-clockwise direction.

Example 2.6.6. Let $A = \begin{bmatrix} k & 0 \\ 0 & k \end{bmatrix}$ for some $k > 0$. Define $L(v) = Av$ for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x, y) = A(x, y) = \begin{bmatrix} k & 0 \\ 0 & k \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} kx \\ ky \end{bmatrix}.$$

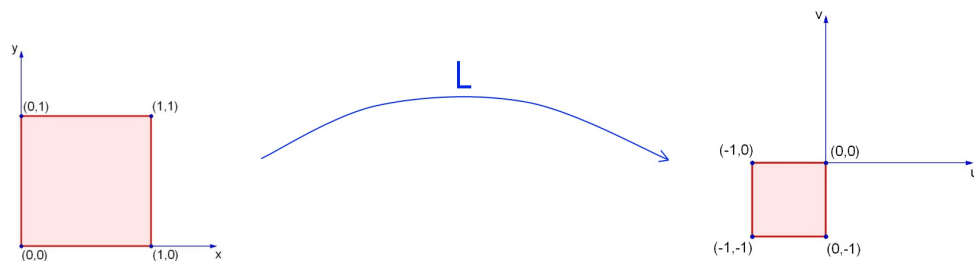
We find $L(0, 0) = (0, 0)$, $L(1, 0) = (k, 0)$, $L(1, 1) = (k, k)$, $L(0, 1) = (0, k)$. This mapping is called a **dilation**.



Example 2.6.7. Let $A = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}$. Define $L(v) = Av$ for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x, y) = A(x, y) = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} -x \\ -y \end{bmatrix}.$$

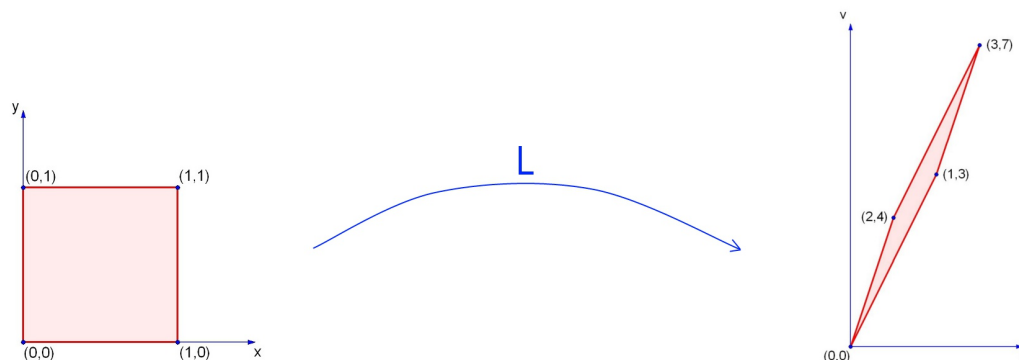
We find $L(0,0) = (0,0)$, $L(1,0) = (-1,0)$, $L(1,1) = (-1,-1)$, $L(0,1) = (0,-1)$. This mapping is called an **inversion**.



Example 2.6.8. Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$. Define $L(v) = Av$ for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x,y) = A(x,y) = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x + 2y \\ 3x + 4y \end{bmatrix}.$$

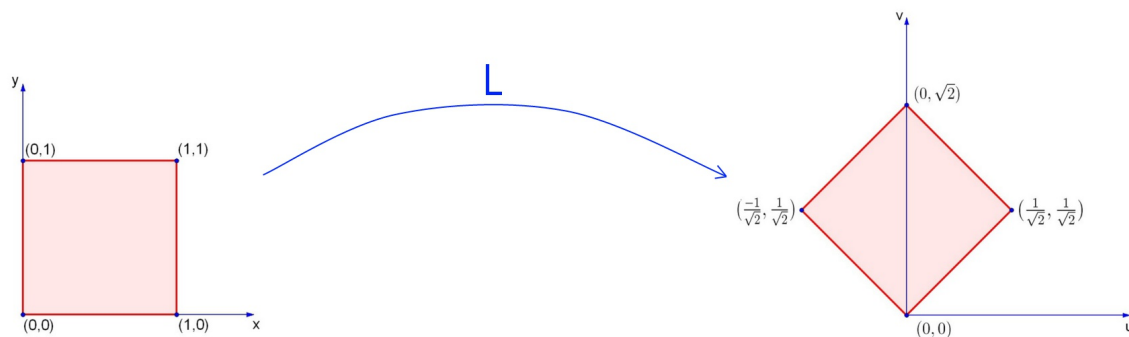
We find $L(0,0) = (0,0)$, $L(1,0) = (1,3)$, $L(1,1) = (3,7)$, $L(0,1) = (2,4)$. This mapping shall remain nameless, it is doubtless a combination of the other named mappings.



Example 2.6.9. Let $A = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$. Define $L(v) = Av$ for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x,y) = A(x,y) = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} x - y \\ x + y \end{bmatrix}.$$

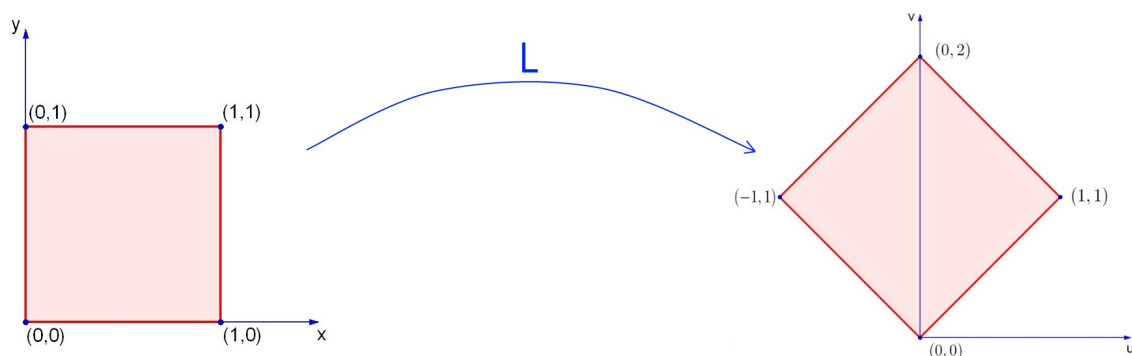
We find $L(0,0) = (0,0)$, $L(1,0) = \frac{1}{\sqrt{2}}(1,1)$, $L(1,1) = \frac{1}{\sqrt{2}}(0,2)$, $L(0,1) = \frac{1}{\sqrt{2}}(-1,1)$. This mapping is a rotation by $\pi/4$ radians.



Example 2.6.10. Let $A = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$. Define $L(v) = Av$ for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x, y) = A(x, y) = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x - y \\ x + y \end{bmatrix}.$$

We find $L(0, 0) = (0, 0)$, $L(1, 0) = (1, 1)$, $L(1, 1) = (0, 2)$, $L(0, 1) = (-1, 1)$. This mapping is a rotation followed by a dilation by $k = \sqrt{2}$.

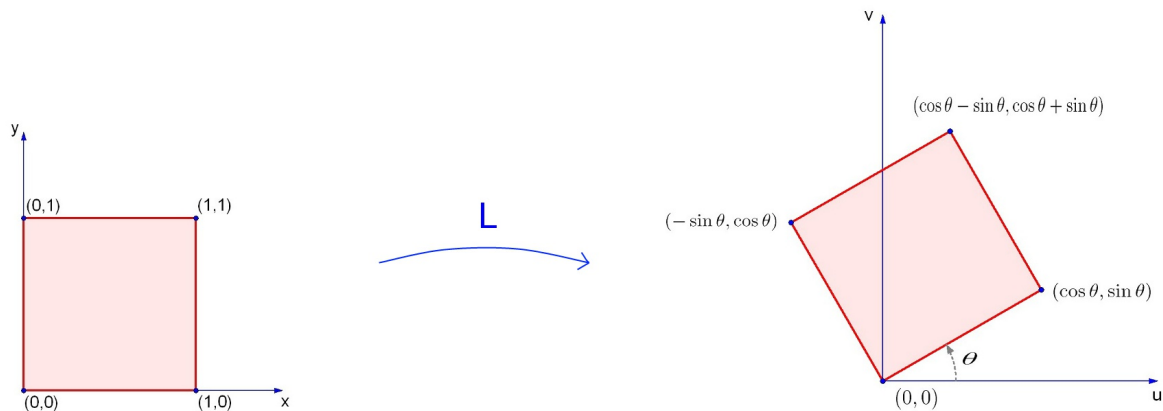


We will come back to discuss rotations a few more times this semester, you'll see they give us interesting and difficult questions later this semester. Also, if you so choose there are a few bonus applied problems on computer graphics which are built from an understanding of the mathematics in the next example.

Example 2.6.11. Let $A = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix}$. Define $L(v) = Av$ for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x, y) = A(x, y) = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x \cos(\theta) - y \sin(\theta) \\ x \sin(\theta) + y \cos(\theta) \end{bmatrix}.$$

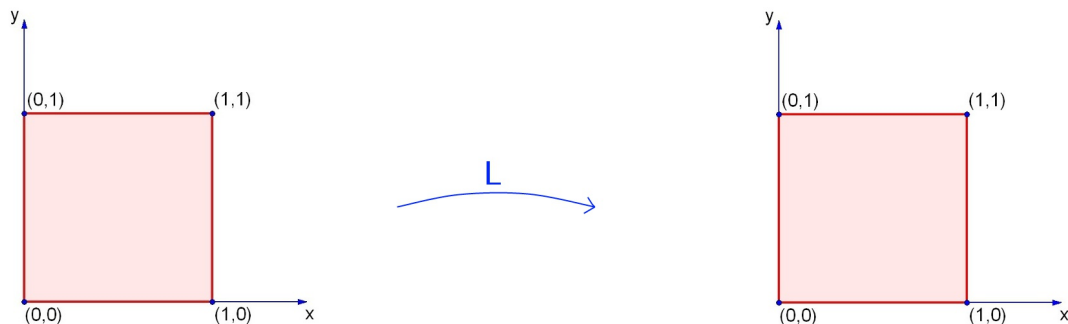
We find $L(0,0) = (0,0)$, $L(1,0) = (\cos(\theta), \sin(\theta))$, $L(1,1) = (\cos(\theta) - \sin(\theta), \cos(\theta) + \sin(\theta))$, $L(0,1) = (\sin(\theta), \cos(\theta))$. This mapping is a rotation by θ in the counter-clockwise direction. Of course you could have derived the matrix A from the picture below.



Example 2.6.12. Let $A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$. Define $L(v) = Av$ for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x, y) = A(x, y) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix}.$$

We find $L(0,0) = (0,0)$, $L(1,0) = (1,0)$, $L(1,1) = (1,1)$, $L(0,1) = (0,1)$. This mapping is a rotation by zero radians, or you could say it is a dilation by a factor of 1, ... usually we call this the identity mapping because the image is identical to the preimage.



Example 2.6.13. Let $A_1 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$. Define $P_1(v) = A_1 v$ for all $v \in \mathbb{R}^2$. In particular this means,

$$P_1(x, y) = A_1(x, y) = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x \\ 0 \end{bmatrix}.$$

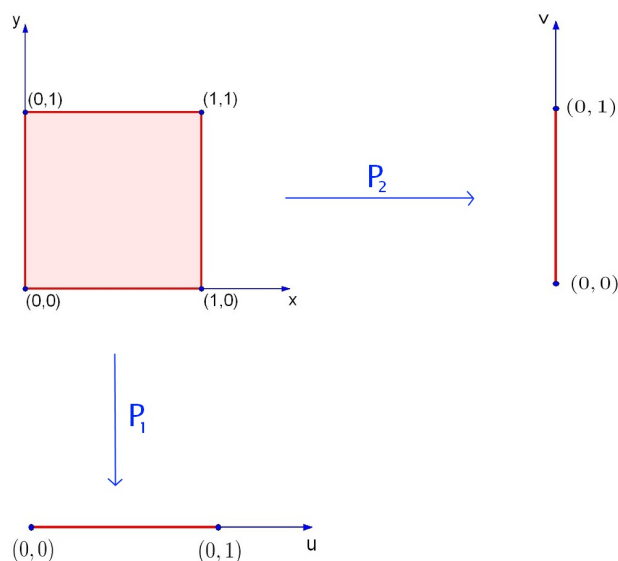
We find $P_1(0, 0) = (0, 0)$, $P_1(1, 0) = (1, 0)$, $P_1(1, 1) = (1, 0)$, $P_1(0, 1) = (0, 0)$. This mapping is a **projection** onto the first coordinate.

Let $A_2 = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$. Define $P_2(v) = A_2 v$ for all $v \in \mathbb{R}^2$. In particular this means,

$$P_2(x, y) = A_2(x, y) = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}.$$

We find $P_2(0, 0) = (0, 0)$, $P_2(1, 0) = (0, 0)$, $P_2(1, 1) = (0, 1)$, $P_2(0, 1) = (0, 1)$. This mapping is a **projection** onto the second coordinate.

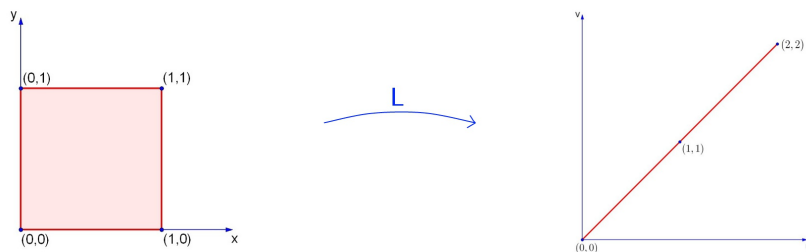
We can picture both of these mappings at once:



Example 2.6.14. Let $A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$. Define $L(v) = Av$ for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x, y) = A(x, y) = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x + y \\ x + y \end{bmatrix}.$$

We find $L(0, 0) = (0, 0)$, $L(1, 0) = (1, 1)$, $L(1, 1) = (2, 2)$, $L(0, 1) = (1, 1)$. This mapping is not a projection, but it does collapse the square to a line-segment.



A projection has to have the property that if it is applied twice then you obtain the same image as if you applied it only once. If you apply the transformation to the image then you'll obtain a line-segment from $(0,0)$ to $(4,4)$. While it is true the transformation "projects" the plane to a line it is not technically a "projection".

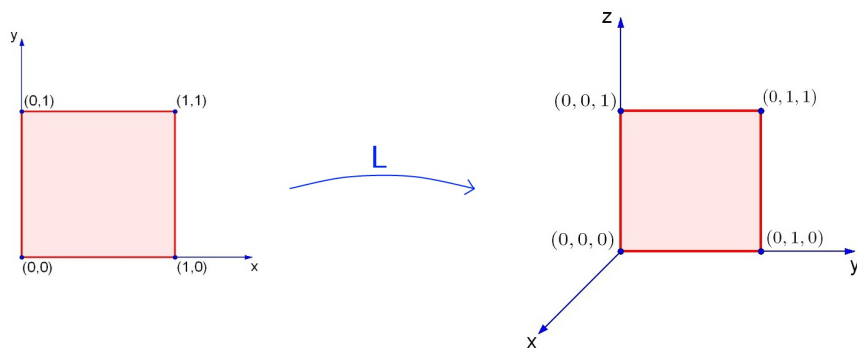
Remark 2.6.15.

The examples here have focused on linear transformations from \mathbb{R}^2 to \mathbb{R}^2 . It turns out that higher dimensional mappings can largely be understood in terms of the geometric operations we've seen in this section.

Example 2.6.16. Let $A = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$. Define $L(v) = Av$ for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x, y) = A(x, y) = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ x \\ y \end{bmatrix}.$$

We find $L(0,0) = (0,0,0)$, $L(1,0) = (0,1,0)$, $L(1,1) = (0,1,1)$, $L(0,1) = (0,0,1)$. This mapping moves the xy -plane to the yz -plane. In particular, the horizontal unit square gets mapped to vertical unit square; $L([0,1] \times [0,1]) = \{0\} \times [0,1] \times [0,1]$. This mapping certainly is not surjective because no point with $x \neq 0$ is covered in the range.



Example 2.6.17. Let $A = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix}$. Define $L(v) = Av$ for all $v \in \mathbb{R}^3$. In particular this means,

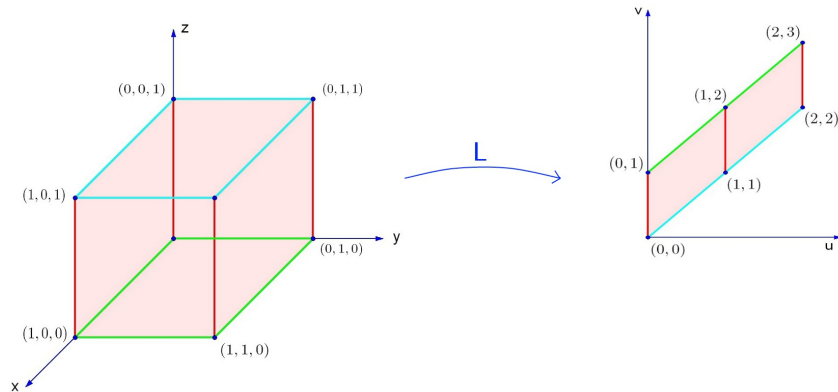
$$L(x, y, z) = A(x, y, z) = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x + y \\ x + y + z \end{bmatrix}.$$

Let's study how L maps the unit cube. We have $2^3 = 8$ corners on the unit cube,

$$L(0, 0, 0) = (0, 0), \quad L(1, 0, 0) = (1, 1), \quad L(1, 1, 0) = (2, 2), \quad L(0, 1, 0) = (1, 1)$$

$$L(0, 0, 1) = (0, 1), \quad L(1, 0, 1) = (1, 2), \quad L(1, 1, 1) = (2, 3), \quad L(0, 1, 1) = (1, 2).$$

This mapping squished the unit cube to a shape in the plane which contains the points $(0, 0)$, $(0, 1)$, $(1, 1)$, $(1, 2)$, $(2, 2)$, $(2, 3)$. Face by face analysis of the mapping reveals the image is a parallelogram. This mapping is certainly not injective since two different points get mapped to the same point. In particular, I have color-coded the mapping of top and base faces as they map to line segments. The vertical faces map to one of the two parallelograms that comprise the image.



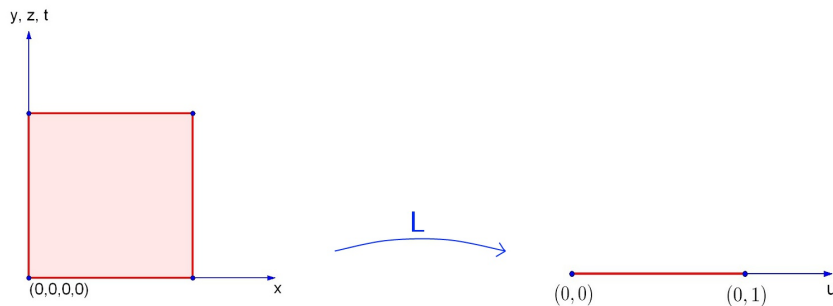
I have used terms like "vertical" or "horizontal" in the standard manner we associate such terms with three dimensional geometry. Visualization and terminology for higher-dimensional examples is not as obvious. However, with a little imagination we can still draw pictures to capture important aspects of mappings.

Example 2.6.18. Let $A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix}$. Define $L(v) = Av$ for all $v \in \mathbb{R}^4$. In particular this means,

$$L(x, y, z, t) = A(x, y, z, t) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ t \end{bmatrix} = \begin{bmatrix} x \\ x \end{bmatrix}.$$

Let's study how L maps the unit hypercube $[0, 1]^4 \subset \mathbb{R}^4$. We have $2^4 = 16$ corners on the unit hypercube, note $L(1, a, b, c) = (1, 1)$ whereas $L(0, a, b, c) = (0, 0)$ for all $a, b, c \in [0, 1]$. Therefore,

the unit hypercube is squished to a line-segment from $(0,0)$ to $(1,1)$. This mapping is neither surjective nor injective. In the picture below the vertical axis represents the y, z, t -directions.



Example 2.6.19. Suppose $f(t, s) = (\sqrt{t}, s^2 + t)$ note that $f(1, 1) = (1, 2)$ and $f(4, 4) = (2, 20)$. Note that $(4, 4) = 4(1, 1)$ thus we should see $f(4, 4) = f(4(1, 1)) = 4f(1, 1)$ but that fails to be true so f is not a linear transformation.

Example 2.6.20. Let $L : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be defined by $L(x) = 0$ for all $x \in V$. This is a linear transformation known as the **trivial transformation**

$$L(x + y) = 0 = 0 + 0 = L(x) + L(y) \quad \text{and} \quad L(cx) = 0 = c0 = cL(x)$$

for all $c \in \mathbb{R}$ and $x, y \in \mathbb{R}^n$.

Example 2.6.21. The identity function on a \mathbb{R}^n is also a linear transformation. Let $Id : \mathbb{R}^n \rightarrow \mathbb{R}^n$ satisfy $L(x) = x$ for each $x \in \mathbb{R}^n$. Observe that

$$Id(x + cy) = x + cy = x + c(y) = Id(x) + cId(y)$$

for all $x, y \in \mathbb{R}^n$ and $c \in \mathbb{R}$.

Example 2.6.22. Let $L(x, y) = x^2 + y^2$ define a mapping from \mathbb{R}^2 to \mathbb{R} . This is not a linear transformation since

$$L(c(x, y)) = L(cx, cy) = (cx)^2 + (cy)^2 = c^2(x^2 + y^2) = c^2L(x, y).$$

We say L is a nonlinear transformation.

Obviously we have not even begun to appreciate the wealth of possibilities that exist for linear mappings. Clearly different types of matrices will describe different types of geometric transformations from \mathbb{R}^n to \mathbb{R}^m . On the other hand, square matrices describe mappings from \mathbb{R}^n to \mathbb{R}^n and these can be thought of as coordinate transformations. A square matrix may give us a way to define new coordinates on \mathbb{R}^n . We will return to the concept of linear transformations a number of times in this course. Hopefully you already appreciate that linear algebra is not just about solving equations. It always comes back to that, but there is more here to ponder.

2.7 properties linear transformations

If you are pondering what I am pondering then you probably would like to know if all linear mappings from \mathbb{R}^n to \mathbb{R}^m can be reduced to matrix multiplication? We saw that if a map is defined as a matrix multiplication then it will be linear. A natural question to ask: is the converse true? Given a linear transformation from \mathbb{R}^n to \mathbb{R}^m can we write the transformation as multiplication by a matrix ?

Theorem 2.7.1. *fundamental theorem of linear algebra.*

$L : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a linear transformation if and only if there exists $A \in \mathbb{R}^{m \times n}$ such that $L(x) = Ax$ for all $x \in \mathbb{R}^n$.

Proof: (\Leftarrow) Assume there exists $A \in \mathbb{R}^{m \times n}$ such that $L(x) = Ax$ for all $x \in \mathbb{R}^n$. As we argued before,

$$L(x + cy) = A(x + cy) = Ax + cAy = L(x) + cL(y)$$

for all $x, y \in \mathbb{R}^n$ and $c \in \mathbb{R}$ hence L is a linear transformation.

(\Rightarrow) Assume $L : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a linear transformation. Let e_i denote the standard basis in \mathbb{R}^n and let f_j denote the standard basis in \mathbb{R}^m . If $x \in \mathbb{R}^n$ then there exist constants x_i such that $x = x_1e_1 + x_2e_2 + \cdots + x_ne_n$ and

$$\begin{aligned} L(x) &= L(x_1e_1 + x_2e_2 + \cdots + x_ne_n) \\ &= x_1L(e_1) + x_2L(e_2) + \cdots + x_nL(e_n) \end{aligned}$$

where we made use of Proposition 6.1.9. Notice $L(e_i) \in \mathbb{R}^m$ thus there exist constants, say A_{ij} , such that

$$L(e_i) = A_{1i}f_1 + A_{2i}f_2 + \cdots + A_{mi}f_m$$

for each $i = 1, 2, \dots, n$. Let's put it all together,

$$\begin{aligned} L(x) &= \sum_{i=1}^n x_i L(e_i) \\ &= \sum_{i=1}^n x_i \sum_{j=1}^m A_{ji} f_j \\ &= \sum_{i=1}^n \sum_{j=1}^m A_{ji} x_i f_j \\ &= Ax. \end{aligned}$$

Notice that $A_{ji} = L(e_i)_j$ for $1 \leq i \leq n$ and $1 \leq j \leq m$ hence $A \in \mathbb{R}^{m \times n}$ by its construction. \square

The fundamental theorem of algebra allows us to make the following definition.

Definition 2.7.2.

Let $L : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be a linear transformation, the matrix $A \in \mathbb{R}^{m \times n}$ such that $L(x) = Ax$ for all $x \in \mathbb{R}^n$ is called the **standard matrix** of L . We denote this by $[L] = A$ or more compactly, $[L_A] = A$, we say that L_A is the linear transformation induced by A . Moreover, the components of the matrix A are found from $A_{ji} = (L(e_i))_j$.

Example 2.7.3. Given that $L([x, y, z]^T) = [x + 2y, 3y + 4z, 5x + 6z]^T$ for $[x, y, z]^T \in \mathbb{R}^3$ find the standard matrix of L . We wish to find a 3×3 matrix such that $L(v) = Av$ for all $v = [x, y, z]^T \in \mathbb{R}^3$. Write $L(v)$ then collect terms with each coordinate in the domain,

$$L\left(\begin{bmatrix} x \\ y \\ z \end{bmatrix}\right) = \begin{bmatrix} x + 2y \\ 3y + 4z \\ 5x + 6z \end{bmatrix} = x \begin{bmatrix} 1 \\ 0 \\ 5 \end{bmatrix} + y \begin{bmatrix} 2 \\ 3 \\ 0 \end{bmatrix} + z \begin{bmatrix} 0 \\ 4 \\ 6 \end{bmatrix}$$

It's not hard to see that,

$$L\left(\begin{bmatrix} x \\ y \\ z \end{bmatrix}\right) = \begin{bmatrix} 1 & 2 & 0 \\ 0 & 3 & 4 \\ 5 & 0 & 6 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} \Rightarrow A = [L] = \begin{bmatrix} 1 & 2 & 0 \\ 0 & 3 & 4 \\ 5 & 0 & 6 \end{bmatrix}$$

Notice that the columns in A are just as you'd expect from the proof of theorem 2.7.1. $[L] = [L(e_1)|L(e_2)|L(e_3)]$. In future examples I will exploit this observation to save writing.

Example 2.7.4. Suppose that $L((t, x, y, z)) = (t + x + y + z, z - x, 0, 3t - z)$, find $[L]$.

$$\begin{aligned} L(e_1) &= L((1, 0, 0, 0)) = (1, 0, 0, 3) \\ L(e_2) &= L((0, 1, 0, 0)) = (1, -1, 0, 0) \\ L(e_3) &= L((0, 0, 1, 0)) = (1, 0, 0, 0) \\ L(e_4) &= L((0, 0, 0, 1)) = (1, 1, 0, -1) \end{aligned} \Rightarrow [L] = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & -1 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 3 & 0 & 0 & -1 \end{bmatrix}.$$

I invite the reader to check my answer here and see that $L(v) = [L]v$ for all $v \in \mathbb{R}^4$ as claimed.

Proposition 2.7.5.

Let $L : \mathbb{R}^n \rightarrow \mathbb{R}^m$ be a linear transformation,

1. $L(0) = 0$
2. $L(c_1v_1 + c_2v_2 + \cdots + c_nv_n) = c_1L(v_1) + c_2L(v_2) + \cdots + c_nL(v_n)$ for all $v_i \in \mathbb{R}^n$ and $c_i \in \mathbb{R}$.

Proof: to prove of (1.) let $x \in \mathbb{R}^n$ and notice that $x - x = 0$ thus

$$L(0) = L(x - x) = L(x) + L(-1x) = L(x) - L(x) = 0.$$

To prove (2.) we use induction on n . Notice the proposition is true for $n=1,2$ by definition of linear transformation. Assume inductively $L(c_1v_1 + c_2v_2 + \cdots + c_nv_n) = c_1L(v_1) + c_2L(v_2) + \cdots + c_nL(v_n)$ for

all $v_i \in \mathbb{R}^n$ and $c_i \in \mathbb{R}$ where $i = 1, 2, \dots, n$. Let $v_1, v_2, \dots, v_n, v_{n+1} \in \mathbb{R}^n$ and $c_1, c_2, \dots, c_n, c_{n+1} \in \mathbb{R}$ and consider, $L(c_1v_1 + c_2v_2 + \dots + c_nv_n + c_{n+1}v_{n+1}) =$

$$\begin{aligned} &= L(c_1v_1 + c_2v_2 + \dots + c_nv_n) + c_{n+1}L(v_{n+1}) && \text{by linearity of } L \\ &= c_1L(v_1) + c_2L(v_2) + \dots + c_nL(v_n) + c_{n+1}L(v_{n+1}) && \text{by the induction hypothesis.} \end{aligned}$$

Hence the proposition is true for $n+1$ and we conclude by the principle of mathematical induction that (2.) is true for all $n \in \mathbb{N}$. \square

Example 2.7.6. Suppose $L : \mathbb{R} \rightarrow \mathbb{R}$ is defined by $L(x) = mx + b$ for some constants $m, b \in \mathbb{R}$. Is this a linear transformation on \mathbb{R} ? Observe:

$$L(0) = m(0) + b = b$$

thus L is not a linear transformation if $b \neq 0$. On the other hand, if $b = 0$ then L is a linear transformation.

Remark 2.7.7.

A mapping on \mathbb{R}^n which has the form $T(x) = x + b$ is called a **translation**. If we have a mapping of the form $F(x) = Ax + b$ for some $A \in \mathbb{R}^{n \times n}$ and $b \in \mathbb{R}^n$ then we say F is an **affine transformation** on \mathbb{R}^n . Technically, in general, the line $y = mx + b$ is the graph of an affine function on \mathbb{R} . I invite the reader to prove that affine transformations also map line-segments to line-segments (or points).

Very well, let's return to the concepts of injective and surjectivity of linear mappings. How do our theorems of LI and spanning inform us about the behaviour of linear transformations? The following pair of theorems summarize the situation nicely. (these are Theorems 11 and 12 from page 88-89 of Lay's text)

Theorem 2.7.8. *linear map is injective iff only zero maps to zero.*

$L : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is an injective linear transformation iff the only solution to the equation $L(x) = 0$ is $x = 0$.

Proof: this is a biconditional statement. I'll prove the converse direction to begin.

(\Leftarrow) Suppose $L(x) = 0$ iff $x = 0$ to begin. Let $a, b \in \mathbb{R}^n$ and suppose $L(a) = L(b)$. By linearity we have $L(a - b) = L(a) - L(b) = 0$ hence $a - b = 0$ therefore $a = b$ and we find L is injective.

(\Rightarrow) Suppose L is injective. Suppose $L(x) = 0$. Note $L(0) = 0$ by linearity of L but then by 1-1 property we have $L(x) = L(0)$ implies $x = 0$ hence the unique solution of $L(x) = 0$ is the zero solution. \square

The theorem above is very important to abstract algebra. It turns out this is also a useful criteria to determine if a homomorphism is a 1-1 mapping. Linear algebra is a prerequisite of abstract because linear algebra provides a robust example of what is abstracted in abstract algebra. The following theorem is special to our context this semester.

Theorem 2.7.9. *linear map is injective iff only zero maps to zero.*

$L : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is a linear transformation with standard matrix $[L]$ then

1. L is 1-1 iff the columns of $[L]$ are linearly independent,
2. L is onto \mathbb{R}^m iff the columns of $[L]$ span \mathbb{R}^m .

Proof: To prove (1.) use Theorem 2.7.8:

$$L \text{ is 1-1} \Leftrightarrow \left\{ L(x) = 0 \Leftrightarrow x = 0 \right\} \Leftrightarrow \left\{ [L]x = 0 \Leftrightarrow x = 0. \right\}$$

and the last equation simply states that if a linear combination of columns of L is zero then the coefficients of that linear equation are zero so (1.) follows.

To prove (2.) recall that Theorem 2.4.15 stated that if $A \in \mathbb{R}^{m \times n}$, $v \in \mathbb{R}^n$ then $Av = b$ is consistent for all $b \in \mathbb{R}^m$ iff the columns of A span \mathbb{R}^m . To say L is onto \mathbb{R}^m means that for each $b \in \mathbb{R}^m$ there exists $v \in \mathbb{R}^n$ such that $L(v) = b$. But, this is equivalent to saying that $[L]v = b$ is consistent for each $b \in \mathbb{R}^m$ so (2.) follows. \square

Example 2.7.10. 1. *You can verify that the linear mappings in Examples 2.6.6, 2.6.7, 2.6.8, 2.6.9, 2.6.10, 2.6.11 and 2.6.12 were both 1-1 and onto. You can see the columns of the transformation matrices were both LI and spanned \mathbb{R}^2 in each of these examples.*

2. *In contrast, Examples 2.6.13 and 2.6.14 were neither 1-1 nor onto. Moreover, the columns of transformation's matrix were linearly dependent in each of these cases and they did not span \mathbb{R}^2 . Instead the span of the columns covered only a particular line in the range.*
3. *In Example 2.6.16 the mapping is injective and the columns of A were indeed linearly independent. However, the columns do not span \mathbb{R}^3 and as expected the mapping is not onto \mathbb{R}^3 .*
4. *In Example 2.6.17 the mapping is not 1-1 and the columns are obviously linearly dependent. On the other hand, the columns of A do span \mathbb{R}^2 and the mapping is onto.*
5. *In Example 2.6.18 the mapping is neither 1-1 nor onto and the columns of the matrix are neither linearly independent nor do they span \mathbb{R}^2 .*

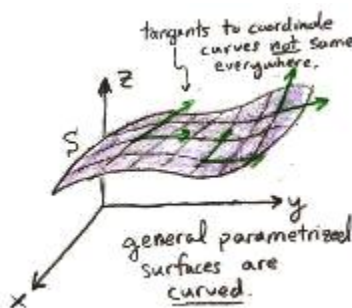
2.8 applications

Geometry is conveniently described by parametrizations. The number of parameters needed to map out some object is the dimension of the object. For example, the rule $t \mapsto \vec{r}(t)$ describes a curve in \mathbb{R}^n . Of course we have the most experience in the cases $\vec{r} = \langle x, y \rangle$ or $\vec{r} = \langle x, y, z \rangle$, these give so-called *planar curves* or *space curves* respectively. Generally, a mapping from $\gamma : \mathbb{R} \rightarrow S$ where S is some space⁹ is called a *path*. The point set $\gamma(S)$ can be identified as a sort of copy of \mathbb{R} which resides in S .

Next, we can consider mappings from \mathbb{R}^2 to some space S . In the case $S = \mathbb{R}^3$ we use $X(u, v) = \langle x(u, v), y(u, v), z(u, v) \rangle$ to parametrize a surface. For example,

$$X(\phi, \theta) = \langle \cos(\theta) \sin(\phi), \sin(\theta) \sin(\phi), \cos(\phi) \rangle$$

parametrizes a sphere if we insist that the angles $0 \leq \theta \leq 2\pi$ and $0 \leq \phi \leq \pi$. We call ϕ and θ coordinates on the sphere, however, these are not coordinates in the technical sense later defined in this course. These are so-called *curvilinear coordinates*. Generally a surface in some space is sort-of a copy of \mathbb{R}^2 (well, to be more precise it resembles some subset of \mathbb{R}^2).



Past the case of a surface we can talk about volumes which are parametrized by three parameters. A volume would have to be embedded into some space which had at least 3 dimensions. For the same reason we can only place a surface in a space with at least 2 dimensions. Perhaps you'd be interested to learn that in relativity theory one considers the world-volume that a particle traces out through spacetime, this is a hyper-volume, it's a 4-dimensional subset of 4-dimensional spacetime.

Let me be a little more technical, if the space we consider is to be a k -dimensional parametric subspace of S then that means there exists an **invertible** mapping $X : U \subseteq \mathbb{R}^k \rightarrow S \subseteq \mathbb{R}^n$. It turns out that for $S = \mathbb{R}^n$ where $n \geq k$ the condition that X be invertible means that the derivative $D_p X : T_p U \rightarrow T_{X(p)} S$ must be an invertible linear mapping at each point p in the parameter space U . This in turn means that the tangent-vectors to the coordinate curves must come together to form a linearly independent set. Linear independence is key.

⁹here S could be a set of matrices or functions or an abstract manifold... the concept of a path is very general

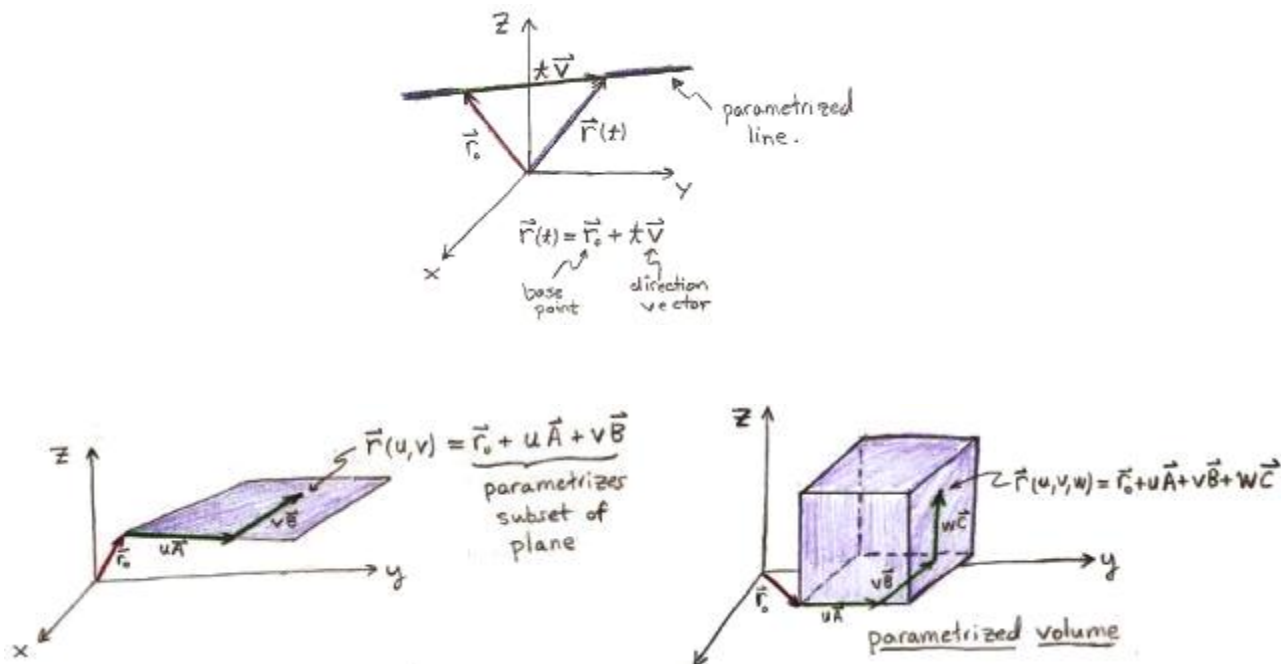
Curvy surfaces and volumes and parametrizations that describe them analytically involve a fair amount of theory which I have only begun to sketch here. However, if we limit our discussion to **affine subspaces** of \mathbb{R}^n we can be explicit. Let me go ahead and write the general form for a line, surface, volume etc... in terms of linearly independent vectors $\vec{A}, \vec{B}, \vec{C}, \dots$

$$\vec{r}(u) = \vec{r}_o + u\vec{A}$$

$$X(u, v) = \vec{r}_o + u\vec{A} + v\vec{B}$$

$$X(u, v, w) = \vec{r}_o + u\vec{A} + v\vec{B} + w\vec{C}$$

I hope you you get the idea.



In each case the parameters give an invertible map only if the vectors are linearly independent. If there was some linear dependence then the dimension of the subspace would collapse. For example,

$$X(u, v) = \langle 1, 1, 1 \rangle + u \langle 1, 0, 1 \rangle + v \langle 2, 0, 2 \rangle$$

appears to give a plane, but upon further inspection you'll notice

$$X(u, v) = \langle 1 + u + 2v, 1, 1 + u + 2v \rangle = \langle 1, 1, 1 \rangle + (u + 2v) \langle 1, 0, 1 \rangle$$

which reveals this is just a line with direction-vector $\langle 1, 0, 1 \rangle$ and parameter $u + 2v$.

2.9 appendix on finite sums

In this appendix we prove a number of seemingly obvious propositions about finite sums of arbitrary size. Most of these statements are "for all $n \in \mathbb{N}$ " thus proof by mathematical induction is the appropriate proof tool. That said, I will abstain from offering a proof for every claim. I offer a few sample arguments and leave the rest to the reader. Let's begin with defining the finite sum:

Definition 2.9.1.

A finite sum of n summands A_1, A_2, \dots, A_n is $A_1 + A_2 + \dots + A_n$. We use "summation notation" or "sigma" notation to write this succinctly:

$$A_1 + A_2 + \dots + A_n = \sum_{i=1}^n A_i$$

The index i is the "dummy index of summation". Technically, we define the sum above recursively. In particular,

$$\sum_{i=1}^{n+1} A_i = A_{n+1} + \sum_{i=1}^n A_i$$

for each $n \geq 1$ and $\sum_{i=1}^1 A_i = A_1$ begins the recursion.

Proposition 2.9.2.

Let $A_i, B_i \in \mathbb{R}$ for each $i \in \mathbb{N}$ and suppose $c \in \mathbb{R}$ then for each $n \in \mathbb{N}$,

$$\begin{aligned} (1.) \quad & \sum_{i=1}^n (A_i + B_i) = \sum_{i=1}^n A_i + \sum_{i=1}^n B_i \\ (2.) \quad & \sum_{i=1}^n cA_i = c \sum_{i=1}^n A_i. \end{aligned}$$

Proof: Let's begin with (1.). Notice the claim is trivially true for $n = 1$. Moreover, $n = 2$ follows from the calculation below:

$$\sum_{i=1}^2 (A_i + B_i) = (A_1 + B_1) + (A_2 + B_2) = (A_1 + A_2) + (B_1 + B_2) = \sum_{i=1}^2 A_i + \sum_{i=1}^2 B_i.$$

Inductively assume that (1.) is true for $n \in \mathbb{N}$. Consider, the following calculations are justified

either from the recursive definition of the finite sum or the induction hypothesis:

$$\begin{aligned}
 \sum_{i=1}^{n+1} (A_i + B_i) &= \sum_{i=1}^n (A_i + B_i) + A_{n+1} + B_{n+1} \\
 &= \left(\sum_{i=1}^n A_i + \sum_{i=1}^n B_i \right) + A_{n+1} + B_{n+1} \\
 &= \left(\sum_{i=1}^n A_i \right) + A_{n+1} + \left(\sum_{i=1}^n B_i \right) + B_{n+1} \\
 &= \sum_{i=1}^{n+1} A_i + \sum_{i=1}^{n+1} B_i.
 \end{aligned}$$

Thus (1.) is true for $n + 1$ and hence by PMI we find (1.) is true for all $n \in \mathbb{N}$. The proof of (2.) is similar. \square

Proposition 2.9.3.

Let $A_i, B_{ij} \in \mathbb{R}$ for $i, j \in \mathbb{N}$ and suppose $c \in \mathbb{R}$ then for each $n \in \mathbb{N}$,

$$\begin{aligned}
 (1.) \quad & \sum_{i=1}^n c = cn \\
 (2.) \quad & \sum_{i=1}^n \sum_{j=1}^n B_{ij} = \sum_{j=1}^n \sum_{i=1}^n B_{ij}. \\
 (3.) \quad & \sum_{i=1}^n \sum_{j=1}^n A_i B_{ij} = \sum_{i=1}^n A_i \sum_{j=1}^n B_{ij} \\
 (4.) \quad & \left(\sum_{i=1}^n A_i \right) c = \sum_{i=1}^n (A_i c).
 \end{aligned}$$

Proof: Let's begin with (1.). Notice the claim is trivially true for $n = 1$. Assume that (1.) is true for a fixed, but arbitrary, $n \in \mathbb{N}$ and consider that

$$\sum_{i=1}^{n+1} c = c + \sum_{i=1}^n c = c + nc = (n + 1)c$$

by the recursive definition of the finite sum and the induction hypothesis. We find that (1.) is true for $n + 1$ hence by PMI (1.) is true for all $n \in \mathbb{N}$.

The proof of (2.) proceeds by induction on n . If $n = 1$ then there is only one possible term, namely B_{11} and the sums trivially agree. Consider the $n = 2$ case as we prepare for the induction step,

$$\sum_{i=1}^2 \sum_{j=1}^2 B_{ij} = \sum_{i=1}^2 [B_{i1} + B_{i2}] = [B_{11} + B_{12}] + [B_{21} + B_{22}]$$

On the other hand,

$$\sum_{j=1}^2 \sum_{i=1}^2 B_{ij} = \sum_{j=1}^2 [B_{1j} + B_{2j}] = [B_{11} + B_{21}] + [B_{12} + B_{22}].$$

The sums in opposite order produce the same terms overall, however the ordering of the terms may differ¹⁰. Fortunately, real number-addition commutes. Assume inductively that (2.) is true for $n \in \mathbb{N}$. Using the definition of sum and the induction hypothesis in the 4-th line:

$$\begin{aligned} \sum_{i=1}^{n+1} \sum_{j=1}^{n+1} B_{ij} &= \sum_{i=1}^{n+1} \left[B_{i,n+1} + \sum_{j=1}^n B_{ij} \right] \\ &= B_{n+1,n+1} + \sum_{j=1}^n B_{n+1,j} + \sum_{i=1}^n \left[B_{i,n+1} + \sum_{j=1}^n B_{ij} \right] \\ &= B_{n+1,n+1} + \sum_{j=1}^n B_{n+1,j} + \sum_{i=1}^n B_{i,n+1} + \sum_{i=1}^n \sum_{j=1}^n B_{ij} \\ &= B_{n+1,n+1} + \sum_{j=1}^n B_{n+1,j} + \sum_{i=1}^n B_{i,n+1} + \sum_{j=1}^n \sum_{i=1}^n B_{ij} \\ &= \sum_{j=1}^{n+1} B_{n+1,j} + \sum_{j=1}^{n+1} \sum_{i=1}^n B_{ij} \\ &= \sum_{j=1}^{n+1} \left[B_{n+1,j} + \sum_{i=1}^n B_{ij} \right] \\ &= \sum_{j=1}^{n+1} \sum_{i=1}^{n+1} B_{ij}. \end{aligned}$$

Thus n implies $n + 1$ for (2.) therefore by PMI we find (2.) is true for all $n \in \mathbb{N}$. The proofs of (3.) and (4.) involve similar induction arguments. \square

¹⁰reordering terms in the infinite series case can get you into trouble if you don't have absolute convergence. Riemann showed a conditionally convergent series can be reordered to force it to converge to any value you might choose.

Remark 2.9.4.

I included this appendix to collect a few common tricks we need to use for proofs involving arbitrary sums. In particular proofs for parts of Theorem 2.3.13 require identities from this appendix. You are free to use the facts in this appendix by referring to them as "a property of finite sums".

Chapter 3

matrix arithmetic

In the preceding chapter I have used some matrix terminology in passing as if you already knew the meaning of such terms as "row", "column" and "matrix". I do hope you have had some previous exposure to basic matrix math, but this chapter should be self-contained. I'll start at the beginning and define all the terms.

3.1 basic terminology and notation

Definition 3.1.1.

An $m \times n$ matrix is an array of numbers with m rows and n columns. The elements in the array are called entries or components. If A is an $m \times n$ matrix then A_{ij} denotes the number in the i -th row and the j -th column. The label i is a row index and the index j is a column index in the preceding sentence. We usually denote $A = [A_{ij}]$. The set of $m \times n$ matrices with real number entries is denoted $\mathbb{R}^{m \times n}$. The set of $m \times n$ matrices with complex entries is $\mathbb{C}^{m \times n}$. If a matrix has the same number of rows and columns then it is called a **square matrix**.

Matrices can be constructed from set-theoretic arguments in much the same way as Cartesian Products. I will not pursue those matters in these notes. We will assume that everyone understands how to construct an array of numbers.

Example 3.1.2. Suppose $A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}$. We see that A has 2 rows and 3 columns thus $A \in \mathbb{R}^{2 \times 3}$. Moreover, $A_{11} = 1$, $A_{12} = 2$, $A_{13} = 3$, $A_{21} = 4$, $A_{22} = 5$, and $A_{23} = 6$. It's not usually possible to find a formula for a generic element in the matrix, but this matrix satisfies $A_{ij} = 3(i - 1) + j$ for all i, j .

In the statement "for all i, j " it is to be understood that those indices range over their allowed values. In the preceding example $1 \leq i \leq 2$ and $1 \leq j \leq 3$.

Definition 3.1.3.

Two matrices A and B are equal if and only if they have the same size and $A_{ij} = B_{ij}$ for all i, j .

If you studied vectors before you should identify this is precisely the same rule we used in calculus III. Two vectors were equal iff all the components matched. Vectors are just specific cases of matrices so the similarity is not surprising.

Definition 3.1.4.

Let $A \in \mathbb{R}^{m \times n}$ then a submatrix of A is a matrix which is made of some rectangle of elements in A . Rows and columns are submatrices. In particular,

1. An $m \times 1$ submatrix of A is called a column vector of A . The j -th **column vector** is denoted $col_j(A)$ and $(col_j(A))_i = A_{ij}$ for $1 \leq i \leq m$. In other words,

$$col_k(A) = \begin{bmatrix} A_{1k} \\ A_{2k} \\ \vdots \\ A_{mk} \end{bmatrix} \Rightarrow A = \begin{bmatrix} A_{11} & A_{21} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{mn} \end{bmatrix} = [col_1(A) | col_2(A) | \cdots | col_n(A)]$$

2. An $1 \times n$ submatrix of A is called a row vector of A . The i -th **row vector** is denoted $row_i(A)$ and $(row_i(A))_j = A_{ij}$ for $1 \leq j \leq n$. In other words,

$$row_k(A) = [A_{k1} \ A_{k2} \ \cdots \ A_{kn}] \Rightarrow A = \begin{bmatrix} A_{11} & A_{21} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{mn} \end{bmatrix} = \begin{bmatrix} row_1(A) \\ row_2(A) \\ \vdots \\ row_m(A) \end{bmatrix}$$

Suppose $A \in \mathbb{R}^{m \times n}$, note for $1 \leq j \leq n$ we have $col_j(A) \in \mathbb{R}^{m \times 1}$ whereas for $1 \leq i \leq m$ we find $row_i(A) \in \mathbb{R}^{1 \times n}$. In other words, an $m \times n$ matrix has n columns of length m and m rows of length n .

Example 3.1.5. Suppose $A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}$. The columns of A are,

$$col_1(A) = \begin{bmatrix} 1 \\ 4 \end{bmatrix}, \quad col_2(A) = \begin{bmatrix} 2 \\ 5 \end{bmatrix}, \quad col_3(A) = \begin{bmatrix} 3 \\ 6 \end{bmatrix}.$$

The rows of A are

$$row_1(A) = [1 \ 2 \ 3], \quad row_2(A) = [4 \ 5 \ 6]$$

Definition 3.1.6.

Let $A \in \mathbb{R}^{m \times n}$ then $A^T \in \mathbb{R}^{n \times m}$ is called the **transpose** of A and is defined by $(A^T)_{ji} = A_{ij}$ for all $1 \leq i \leq m$ and $1 \leq j \leq n$.

Example 3.1.7. Suppose $A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}$ then $A^T = \begin{bmatrix} 1 & 4 \\ 2 & 5 \\ 3 & 6 \end{bmatrix}$. Notice that

$$\text{row}_1(A) = \text{col}_1(A^T), \text{row}_2(A) = \text{col}_2(A^T)$$

and

$$\text{col}_1(A) = \text{row}_1(A^T), \text{col}_2(A) = \text{row}_2(A^T), \text{col}_3(A) = \text{row}_3(A^T)$$

Notice $(A^T)_{ij} = A_{ji} = 3(j-1) + i$ for all i, j ; at the level of index calculations we just switch the indices to create the transpose.

The preceding example shows us that we can quickly create the transpose of a given matrix by switching rows to columns. The transpose of a row vector is a column vector and vice-versa.

3.2 addition and multiplication by scalars

Definition 3.2.1.

Let $A, B \in \mathbb{R}^{m \times n}$ then $A+B \in \mathbb{R}^{m \times n}$ is defined by $(A+B)_{ij} = A_{ij} + B_{ij}$ for all $1 \leq i \leq m$, $1 \leq j \leq n$. If two matrices A, B are not of the same size then their sum is not defined.

Example 3.2.2. Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ and $B = \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix}$. We calculate

$$A + B = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} + \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix} = \begin{bmatrix} 6 & 8 \\ 10 & 12 \end{bmatrix}.$$

Definition 3.2.3.

Let $A, B \in \mathbb{R}^{m \times n}, c \in \mathbb{R}$ then $cA \in \mathbb{R}^{m \times n}$ is defined by $(cA)_{ij} = cA_{ij}$ for all $1 \leq i \leq m$, $1 \leq j \leq n$. We call the process of multiplying A by a number c **multiplication by a scalar**. We define $A-B \in \mathbb{R}^{m \times n}$ by $A-B = A+(-1)B$ which is equivalent to $(A-B)_{ij} = A_{ij} - B_{ij}$ for all i, j .

Example 3.2.4. Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ and $B = \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix}$. We calculate

$$A - B = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} - \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix} = \begin{bmatrix} -4 & -4 \\ -4 & -4 \end{bmatrix}.$$

Now multiply A by the scalar 5,

$$5A = 5 \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} = \begin{bmatrix} 5 & 10 \\ 15 & 20 \end{bmatrix}$$

Example 3.2.5. Let $A, B \in \mathbb{R}^{m \times n}$ be defined by $A_{ij} = 3i + 5j$ and $B_{ij} = i^2$ for all i, j . Then we can calculate $(A + B)_{ij} = 3i + 5j + i^2$ for all i, j .

Definition 3.2.6.

The **zero matrix** in $\mathbb{R}^{m \times n}$ is denoted 0 and defined by $0_{ij} = 0$ for all i, j . The additive inverse of $A \in \mathbb{R}^{m \times n}$ is the matrix $-A$ such that $A + (-A) = 0$. The components of the additive inverse matrix are given by $(-A)_{ij} = -A_{ij}$ for all i, j .

The zero matrix joins a long list of other objects which are all denoted by 0 . Usually the meaning of 0 is clear from the context, the size of the zero matrix is chosen as to be consistent with the equation in which it is found.

Example 3.2.7. Solve the following matrix equation,

$$0 = \begin{bmatrix} x & y \\ z & w \end{bmatrix} + \begin{bmatrix} -1 & -2 \\ -3 & -4 \end{bmatrix} \Rightarrow \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} x-1 & y-2 \\ z-3 & w-4 \end{bmatrix}$$

The definition of matrix equality means this single matrix equation reduces to 4 scalar equations: $0 = x - 1, 0 = y - 2, 0 = z - 3, 0 = w - 4$. The solution is $x = 1, y = 2, z = 3, w = 4$.

Theorem 3.2.8.

If $A \in \mathbb{R}^{m \times n}$ then

1. $0 \cdot A = 0$, (where 0 on the L.H.S. is the number zero)
2. $0A = 0$,
3. $A + 0 = 0 + A = A$.

Proof: I'll prove (2.). Let $A \in \mathbb{R}^{m \times n}$ and consider

$$(0A)_{ij} = \sum_{k=1}^m 0_{ik} A_{kj} = \sum_{k=1}^m 0 A_{kj} = \sum_{k=1}^m 0 = 0$$

for all i, j . Thus $0A = 0$. I leave the other parts to the reader, the proofs are similar. \square

We can add, subtract and scalar multiply linear transformations. Let me define these:

Definition 3.2.9.

Suppose $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ and $S : \mathbb{R}^n \rightarrow \mathbb{R}^m$ are linear transformations then we define $T + S, T - S$ and cT for any $c \in \mathbb{R}$ by the rules

$$(T + S)(x) = T(x) + S(x). \quad (T - S)(x) = T(x) - S(x), \quad (cT)(x) = cT(x)$$

for all $x \in \mathbb{R}^n$.

The following does say something new. Notice I'm talking about adding the transformations themselves not the points in the domain or range.

Proposition 3.2.10.

The sum, difference or scalar multiple of a linear transformations from \mathbb{R}^n to \mathbb{R}^m are once more a linear transformation from \mathbb{R}^n to \mathbb{R}^m .

Proof: I'll be greedy and prove all three at once:

$$\begin{aligned}
 (T + cS)(x + by) &= T(x + by) + (cS)(x + by) && \text{defn. of sum of transformations} \\
 &= T(x + by) + cS(x + by) && \text{defn. of scalar mult. of transformations} \\
 &= T(x) + bT(y) + c[S(x) + bS(y)] && \text{linearity of } S \text{ and } T \\
 &= T(x) + cS(x) + b[T(y) + cS(y)] && \text{vector algebra props.} \\
 &= (T + cS)(x) + b(T + cS)(y) && \text{again, defn. of sum and scal. mult. of trans.}
 \end{aligned}$$

Let $c = 1$ and $b = 1$ to see $T + S$ is additive. Let $c = 1$ and $x = 0$ to see $T + S$ is homogeneous. Let $c = -1$ and $b = 1$ to see $T - S$ is additive. Let $c = -1$ and $x = 0$ to see $T - S$ is homogeneous. Finally, let $T = 0$ to see cS is additive ($b = 1$) and homogeneous ($x = 0$). \square

Proposition 3.2.11.

Suppose $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$ and $S : \mathbb{R}^n \rightarrow \mathbb{R}^m$ are linear transformations then

$$(1.) [T + S] = [T] + [S], \quad (2.) [T - S] = [T] - [S], \quad (3.) [cT] = c[T].$$

In words, the standard matrix of the sum, difference or scalar multiple of linear transformations is the sum, difference or scalar multiple of the standard matrices of the respective linear transformations.

Proof: Note $(T + cS)(e_j) = T(e_j) + cS(e_j)$ hence $((T + cS)(e_j))_i = (T(e_j))_i + c(S(e_j))_i$ for all i, j hence $[T + cS] = [T] + c[S]$. \square

Example 3.2.12. Suppose $T(x, y) = (x + y, x - y)$ and $S(x, y) = (2x, 3y)$. It's easy to see that

$$[T] = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \quad \text{and} \quad [S] = \begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix} \quad \Rightarrow \quad [T + S] = [T] + [S] = \begin{bmatrix} 3 & 1 \\ 1 & 2 \end{bmatrix}$$

Therefore, $(T + S)(x, y) = \begin{bmatrix} 3 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 3x + y \\ x + 2y \end{bmatrix} = (3x + y, x + 2y)$. Naturally this is the same formula that we would obtain through direct addition of the formulas of T and S .

3.3 matrix multiplication

The definition of matrix multiplication is natural for a variety of reasons. Let's think about composing two linear transformations. This will lead us to a natural definition.

Proposition 3.3.1.

$L_1 : \mathbb{R}^m \rightarrow \mathbb{R}^n$ and $L_2 : \mathbb{R}^n \rightarrow \mathbb{R}^p$ are linear transformations then $L_2 \circ L_1 : \mathbb{R}^m \rightarrow \mathbb{R}^p$ is a linear transformation with matrix $[L_2 \circ L_1]$ such that

$$[L_2 \circ L_1]_{ij} = \sum_{k=1}^n [L_2]_{ik} [L_1]_{kj}$$

for all $i = 1, 2, \dots, p$ and $j = 1, 2, \dots, m$.

Proof: Let $x, y \in V_1$ and $c \in \mathbb{R}$,

$$\begin{aligned} (L_2 \circ L_1)(x + cy) &= L_2(L_1(x + cy)) && \text{defn. of composite} \\ &= L_2(L_1(x) + cL_1(y)) && L_1 \text{ is linear trans.} \\ &= L_2(L_1(x)) + cL_2(L_1(y)) && L_2 \text{ is linear trans.} \\ &= (L_2 \circ L_1)(x) + c(L_2 \circ L_1)(y) && \text{defn. of composite} \end{aligned}$$

thus $L_2 \circ L_1$ is a linear transformation. To find the matrix of the composite we need only calculate its action on the standard basis: by definition, $[L_2 \circ L_1]_{ij} = ((L_2 \circ L_1)(e_j))_i$, observe

$$\begin{aligned} (L_2 \circ L_1)(e_j) &= L_2(L_1(e_j)) \\ &= L_2([L_1]e_j) \\ &= L_2\left(\sum_k [L_1]_{kj} e_k\right) \\ &= \sum_k [L_1]_{kj} L_2(e_k) \\ &= \sum_k [L_1]_{kj} [L_2]e_k \\ &= \sum_k [L_1]_{kj} \sum_i [L_2]_{ik} e_i \\ &= \sum_k \sum_i [L_2]_{ik} [L_1]_{kj} e_i \\ &= \sum_i \left[\sum_k [L_2]_{ik} [L_1]_{kj} \right] e_i. \end{aligned}$$

Therefore, $[L_2 \circ L_1]_{ij} = \sum_k [L_2]_{ik} [L_1]_{kj}$ and Item (2.) follows. \square

I have made extensive use of the properties of finite summations in the proof above. Consult the Appendix if you would like to see further details on how to prove claims about finite sums. In short, there are several induction arguments implicit in the calculations above.

Definition 3.3.2.

Let $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times p}$ then the product of A and B is denoted by juxtaposition AB and $AB \in \mathbb{R}^{m \times p}$ is defined by:

$$(AB)_{ij} = \sum_{k=1}^n A_{ik}B_{kj}$$

for each $1 \leq i \leq m$ and $1 \leq j \leq p$. In the case $m = p = 1$ the indices i, j are omitted in the equation since the matrix product is simply a number which needs no index.

This definition is very nice for general proofs, but pragmatically I usually think of matrix multiplication in terms of *dot-products*. Recall $v \cdot w = v_1w_1 + v_2w_2 + \cdots + v_nw_n = \sum_{k=1}^n v_kw_k$.

Proposition 3.3.3.

Let $v, w \in \mathbb{R}^n$ then $v \cdot w = v^T w$.

Proof: Since v^T is an $1 \times n$ matrix and w is an $n \times 1$ matrix the definition of matrix multiplication indicates $v^T w$ should be a 1×1 matrix which is a number. Note in this case the outside indices ij are absent in the boxed equation so the equation reduces to

$$v^T w = v^T_1 w_1 + v^T_2 w_2 + \cdots + v^T_n w_n = v_1 w_1 + v_2 w_2 + \cdots + v_n w_n = v \cdot w. \square$$

Proposition 3.3.4.

The formula given below is equivalent to the Definition 3.3.2. Let $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times p}$ then

$$AB = \begin{bmatrix} \text{row}_1(A) \cdot \text{col}_1(B) & \text{row}_1(A) \cdot \text{col}_2(B) & \cdots & \text{row}_1(A) \cdot \text{col}_p(B) \\ \text{row}_2(A) \cdot \text{col}_1(B) & \text{row}_2(A) \cdot \text{col}_2(B) & \cdots & \text{row}_2(A) \cdot \text{col}_p(B) \\ \vdots & \vdots & \cdots & \vdots \\ \text{row}_m(A) \cdot \text{col}_1(B) & \text{row}_m(A) \cdot \text{col}_2(B) & \cdots & \text{row}_m(A) \cdot \text{col}_p(B) \end{bmatrix}$$

Proof: The formula above claims $(AB)_{ij} = \text{row}_i(A) \cdot \text{col}_j(B)$ for all i, j . Recall that $(\text{row}_i(A))_k = A_{ik}$ and $(\text{col}_j(B))_k = B_{kj}$ thus

$$(AB)_{ij} = \sum_{k=1}^n A_{ik}B_{kj} = \sum_{k=1}^n (\text{row}_i(A))_k (\text{col}_j(B))_k$$

Hence, using definition of the dot-product, $(AB)_{ij} = \text{row}_i(A) \cdot \text{col}_j(B)$. This argument holds for all i, j therefore the Proposition is true. \square

Example 3.3.5. *The product of a 3×2 and 2×3 is a 3×3*

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} = \begin{bmatrix} [1,0][4,7]^T & [1,0][5,8]^T & [1,0][6,9]^T \\ [0,1][4,7]^T & [0,1][5,8]^T & [0,1][6,9]^T \\ [0,0][4,7]^T & [0,0][5,8]^T & [0,0][6,9]^T \end{bmatrix} = \begin{bmatrix} 4 & 5 & 6 \\ 7 & 8 & 9 \\ 0 & 0 & 0 \end{bmatrix}$$

Example 3.3.6. *The product of a 3×1 and 1×3 is a 3×3*

$$\begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \begin{bmatrix} 4 & 5 & 6 \end{bmatrix} = \begin{bmatrix} 4 \cdot 1 & 5 \cdot 1 & 6 \cdot 1 \\ 4 \cdot 2 & 5 \cdot 2 & 6 \cdot 2 \\ 4 \cdot 3 & 5 \cdot 3 & 6 \cdot 3 \end{bmatrix} = \begin{bmatrix} 4 & 5 & 6 \\ 8 & 10 & 12 \\ 12 & 15 & 18 \end{bmatrix}$$

Example 3.3.7. *Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ and $B = \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix}$. We calculate*

$$\begin{aligned} AB &= \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix} \\ &= \begin{bmatrix} [1,2][5,7]^T & [1,2][6,8]^T \\ [3,4][5,7]^T & [3,4][6,8]^T \end{bmatrix} \\ &= \begin{bmatrix} 5 + 14 & 6 + 16 \\ 15 + 28 & 18 + 32 \end{bmatrix} \\ &= \begin{bmatrix} 19 & 22 \\ 43 & 50 \end{bmatrix} \end{aligned}$$

Notice the product of square matrices is square. For numbers $a, b \in \mathbb{R}$ it we know the product of a and b is commutative ($ab = ba$). Let's calculate the product of A and B in the opposite order,

$$\begin{aligned} BA &= \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \\ &= \begin{bmatrix} [5,6][1,3]^T & [5,6][2,4]^T \\ [7,8][1,3]^T & [7,8][2,4]^T \end{bmatrix} \\ &= \begin{bmatrix} 5 + 18 & 10 + 24 \\ 7 + 24 & 14 + 32 \end{bmatrix} \\ &= \begin{bmatrix} 23 & 34 \\ 31 & 46 \end{bmatrix} \end{aligned}$$

*Clearly $AB \neq BA$ thus matrix multiplication is **noncommutative** or **nonabelian**.*

Let's see once more how this definition ties in with the composition of linear mappings:

Example 3.3.8. Let $T : \mathbb{R}^{2 \times 1} \rightarrow \mathbb{R}^{2 \times 1}$ be defined by

$$T([x, y]^T) = [x + y, 2x - y]^T$$

for all $[x, y]^T \in \mathbb{R}^{2 \times 1}$. Also let $S : \mathbb{R}^{2 \times 1} \rightarrow \mathbb{R}^{3 \times 1}$ be defined by

$$S([x, y]^T) = [x, x, 3x + 4y]^T$$

for all $[x, y]^T \in \mathbb{R}^{2 \times 1}$. We calculate the composite as follows:

$$\begin{aligned} (S \circ T)([x, y]^T) &= S(T([x, y]^T)) \\ &= S([x + y, 2x - y]^T) \\ &= [x + y, x + y, 3(x + y) + 4(2x - y)]^T \\ &= [x + y, x + y, 11x - y]^T \end{aligned}$$

Notice we can write the formula above as a matrix multiplication,

$$(S \circ T)([x, y]^T) = \begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 11 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \Rightarrow [S \circ T] = \begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 11 & -1 \end{bmatrix}.$$

Notice that the standard matrices of S and T are:

$$[S] = \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 3 & 4 \end{bmatrix} \quad [T] = \begin{bmatrix} 1 & 1 \\ 2 & -1 \end{bmatrix}$$

It's easy to see that $[S \circ T] = [S][T]$ (as we should expect since these are linear operators)

Notice that $T \circ S$ is not even defined since the dimensions of the codomain of S do not match the domain of T . Likewise, the matrix product $[T][S]$ is not defined since there is a dimension mismatch; $(2 \times 2)(3 \times 2)$ is not a well-defined product of matrices.

When we say that matrix multiplication is noncommutative that indicates that the product of two matrices does not *generally* commute. However, there are special matrices which commute with other matrices.

Example 3.3.9. Let $I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ and $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$. We calculate

$$IA = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

Likewise calculate,

$$AI = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

Since the matrix A was arbitrary we conclude that $IA = AI$ for all $A \in \mathbb{R}^{2 \times 2}$.

Definition 3.3.10.

The identity matrix in $\mathbb{R}^{n \times n}$ is the $n \times n$ square matrix I which has components $I_{ij} = \delta_{ij}$. The notation I_n is sometimes used if the size of the identity matrix needs emphasis, otherwise the size of the matrix I is to be understood from the context.

$$I_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad I_3 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad I_4 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Example 3.3.11. The product of a 2×2 and 2×1 is a 2×1 . Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ and let $v = \begin{bmatrix} 5 \\ 7 \end{bmatrix}$,

$$Av = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 5 \\ 7 \end{bmatrix} = \begin{bmatrix} [1, 2][5, 7]^T \\ [3, 4][5, 7]^T \end{bmatrix} = \begin{bmatrix} 19 \\ 43 \end{bmatrix}$$

Likewise, define $w = \begin{bmatrix} 6 \\ 8 \end{bmatrix}$ and calculate

$$Aw = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 6 \\ 8 \end{bmatrix} = \begin{bmatrix} [1, 2][6, 8]^T \\ [3, 4][6, 8]^T \end{bmatrix} = \begin{bmatrix} 22 \\ 50 \end{bmatrix}$$

Something interesting to observe here, recall that in Example 3.3.7 we calculated

$AB = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix} = \begin{bmatrix} 19 & 22 \\ 43 & 50 \end{bmatrix}$. But these are the same numbers we just found from the two matrix-vector products calculated above. We identify that B is just the **concatenation** of the vectors v and w ; $B = [v|w] = \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix}$. Observe that:

$$AB = A[v|w] = [Av|Aw].$$

The term **concatenate** is sometimes replaced with the word **adjoin**. I think of the process as gluing matrices together. This is an important operation since it allows us to lump together many solutions into a single matrix of solutions. (I will elaborate on that in detail in a future section)

Proposition 3.3.12.

Let $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times p}$ then we can understand the matrix multiplication of A and B as the concatenation of several matrix-vector products,

$$AB = A[\text{col}_1(B)|\text{col}_2(B)|\cdots|\text{col}_p(B)] = [A\text{col}_1(B)|A\text{col}_2(B)|\cdots|A\text{col}_p(B)]$$

Proof: see the Problem Set. You should be able to follow the same general strategy as the Proof of Proposition 3.3.4. Show that the i, j -th entry of the L.H.S. is equal to the matching entry on the R.H.S. Good hunting. \square

There are actually many many different ways to perform the calculation of matrix multiplication. Proposition 3.3.12 essentially parses the problem into a bunch of (matrix)(column vector) calculations. You could go the other direction and view AB as a bunch of (row vector)(matrix) products glued together. In particular,

Proposition 3.3.13.

Let $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times p}$ then we can understand the matrix multiplication of A and B as the concatenation of several matrix-vector products,

$$AB = \begin{bmatrix} \text{row}_1(A) \\ \text{row}_2(A) \\ \vdots \\ \text{row}_m(A) \end{bmatrix} B = \begin{bmatrix} \text{row}_1(A)B \\ \text{row}_2(A)B \\ \vdots \\ \text{row}_m(A)B \end{bmatrix}.$$

Proof: left to reader, but if you ask I'll show you. \square

There are stranger ways to calculate the product. You can also assemble the product by adding together a bunch of outer-products of the rows of A with the columns of B . The dot-product of two vectors is an example of an inner product and we saw $v \cdot w = v^T w$. The outer-product of two vectors goes the other direction: given $v \in \mathbb{R}^n$ and $w \in \mathbb{R}^m$ we find $vw^T \in \mathbb{R}^{n \times m}$.

Proposition 3.3.14. *matrix multiplication as sum of outer products.*

Let $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times p}$ then

$$AB = \text{col}_1(A)\text{row}_1(B) + \text{col}_2(A)\text{row}_2(B) + \cdots + \text{col}_n(A)\text{row}_n(B).$$

Proof: consider the i, j -th component of AB , by definition we have

$$(AB)_{ij} = \sum_{k=1}^n A_{ik}B_{kj} = A_{i1}B_{1j} + A_{i2}B_{2j} + \cdots + A_{in}B_{nj}$$

but note that $(\text{col}_k(A)\text{row}_k(B))_{ij} = \text{col}_k(A)_i \text{row}_k(B)_j = A_{ik}B_{kj}$ for each $k = 1, 2, \dots, n$ and the proposition follows. \square

In the section on block multiplication we will find many other ways to parse a matrix multiplication. My point? These patterns are worth knowing about for future problems. In practice I almost always just calculate by the dot-product method detailed in Proposition 3.3.4

Example 3.3.15. Consider A, v, w from Example 3.3.11.

$$v + w = \begin{bmatrix} 5 \\ 7 \end{bmatrix} + \begin{bmatrix} 6 \\ 8 \end{bmatrix} = \begin{bmatrix} 11 \\ 15 \end{bmatrix}$$

Using the above we calculate,

$$A(v + w) = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 11 \\ 15 \end{bmatrix} = \begin{bmatrix} 11 + 30 \\ 33 + 60 \end{bmatrix} = \begin{bmatrix} 41 \\ 93 \end{bmatrix}.$$

In contrast, we can add Av and Aw ,

$$Av + Aw = \begin{bmatrix} 19 \\ 43 \end{bmatrix} + \begin{bmatrix} 22 \\ 50 \end{bmatrix} = \begin{bmatrix} 41 \\ 93 \end{bmatrix}.$$

Behold, $A(v + w) = Av + Aw$ for this example. It turns out this is true in general.

I collect all my favorite properties for matrix multiplication in the theorem below. To summarize, matrix math works as you would expect with the exception that matrix multiplication is not commutative. We must be careful about the order of letters in matrix expressions.

Theorem 3.3.16.

If $A, B, C \in \mathbb{R}^{m \times n}$, $X, Y \in \mathbb{R}^{n \times p}$, $Z \in \mathbb{R}^{p \times q}$ and $c_1, c_2 \in \mathbb{R}$ then

1. $(A + B) + C = A + (B + C)$,
2. $(AX)Z = A(XZ)$,
3. $A + B = B + A$,
4. $c_1(A + B) = c_1A + c_2B$,
5. $(c_1 + c_2)A = c_1A + c_2A$,
6. $(c_1c_2)A = c_1(c_2A)$,
7. $(c_1A)X = c_1(AX) = A(c_1X) = (AX)c_1$,
8. $1A = A$,
9. $I_m A = A = A I_n$,
10. $A(X + Y) = AX + AY$,
11. $A(c_1X + c_2Y) = c_1AX + c_2AY$,
12. $(A + B)X = AX + BX$,

Proof: I will prove a couple of these and relegate most of the rest to the Problem Set. They actually make pretty fair proof-type test questions. Nearly all of these properties are proved by breaking the statement down to components then appealing to a property of real numbers. Just a reminder, we assume that it is known that \mathbb{R} is an ordered field. Multiplication of real numbers is commutative, associative and distributes across addition of real numbers. Likewise, addition of

real numbers is commutative, associative and obeys familiar distributive laws when combined with addition.

Proof of (1.): assume A, B, C are given as in the statement of the Theorem. Observe that

$$\begin{aligned}
 ((A + B) + C)_{ij} &= (A + B)_{ij} + C_{ij} && \text{defn. of matrix add.} \\
 &= (A_{ij} + B_{ij}) + C_{ij} && \text{defn. of matrix add.} \\
 &= A_{ij} + (B_{ij} + C_{ij}) && \text{assoc. of real numbers} \\
 &= A_{ij} + (B + C)_{ij} && \text{defn. of matrix add.} \\
 &= (A + (B + C))_{ij} && \text{defn. of matrix add.}
 \end{aligned}$$

for all i, j . Therefore $(A + B) + C = A + (B + C)$. \square

Proof of (6.): assume c_1, c_2, A are given as in the statement of the Theorem. Observe that

$$\begin{aligned}
 ((c_1 c_2)A)_{ij} &= (c_1 c_2)A_{ij} && \text{defn. scalar multiplication.} \\
 &= c_1(c_2 A_{ij}) && \text{assoc. of real numbers} \\
 &= (c_1(c_2 A))_{ij} && \text{defn. scalar multiplication.}
 \end{aligned}$$

for all i, j . Therefore $(c_1 c_2)A = c_1(c_2 A)$. \square

Proof of (10.): assume A, X, Y are given as in the statement of the Theorem. Observe that

$$\begin{aligned}
 ((A(X + Y))_{ij} &= \sum_k A_{ik}(X + Y)_{kj} && \text{defn. matrix multiplication,} \\
 &= \sum_k A_{ik}(X_{kj} + Y_{kj}) && \text{defn. matrix addition,} \\
 &= \sum_k (A_{ik}X_{kj} + A_{ik}Y_{kj}) && \text{dist. of real numbers,} \\
 &= \sum_k A_{ik}X_{kj} + \sum_k A_{ik}Y_{kj} && \text{prop. of finite sum,} \\
 &= (AX)_{ij} + (AY)_{ij} && \text{defn. matrix multiplication}(\times 2), \\
 &= (AX + AY)_{ij} && \text{defn. matrix addition,}
 \end{aligned}$$

for all i, j . Therefore $A(X + Y) = AX + AY$. \square

The proofs of the other items are similar, we consider the i, j -th component of the identity and then apply the definition of the appropriate matrix operation's definition. This reduces the problem to a statement about real numbers so we can use the properties of real numbers at the level of components. Then we reverse the steps. Since the calculation works for arbitrary i, j it follows the the matrix equation holds true. This Theorem provides a foundation for later work where we may find it convenient to prove a statement without resorting to a proof by components. Which method of proof is best depends on the question. However, I can't see another way of proving most of 3.3.16.

3.4 elementary matrices

Gauss Jordan elimination consists of three *elementary row operations*:

$$(1.) r_i + ar_j \rightarrow r_i, \quad (2.) br_i \rightarrow r_i, \quad (3.) r_i \leftrightarrow r_j$$

Left multiplication by **elementary matrices** will accomplish the same operation on a matrix.

Definition 3.4.1.

Let $[A : r_i + ar_j \rightarrow r_i]$ denote the matrix produced by replacing row i of matrix A with $row_i(A) + arow_j(A)$. Also define $[A : br_i \rightarrow r_i]$ and $[A : r_i \leftrightarrow r_j]$ in the same way. Let $a, b \in \mathbb{R}$ and $b \neq 0$. The following matrices are called **elementary matrices**:

$$E_{r_i+ar_j \rightarrow r_i} = [I : r_i + ar_j \rightarrow r_i]$$

$$E_{br_i \rightarrow r_i} = [I : br_i \rightarrow r_i]$$

$$E_{r_i \leftrightarrow r_j} = [I : r_i \leftrightarrow r_j]$$

Example 3.4.2. Let $A = \begin{bmatrix} a & b & c \\ 1 & 2 & 3 \\ u & m & e \end{bmatrix}$

$$E_{r_2+3r_1 \rightarrow r_2} A = \begin{bmatrix} 1 & 0 & 0 \\ 3 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a & b & c \\ 1 & 2 & 3 \\ u & m & e \end{bmatrix} = \begin{bmatrix} a & b & c \\ 3a+1 & 3b+2 & 3c+3 \\ u & m & e \end{bmatrix}$$

$$E_{7r_2 \rightarrow r_2} A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 7 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a & b & c \\ 1 & 2 & 3 \\ u & m & e \end{bmatrix} = \begin{bmatrix} a & b & c \\ 7 & 14 & 21 \\ u & m & e \end{bmatrix}$$

$$E_{r_2 \rightarrow r_3} A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} a & b & c \\ 1 & 2 & 3 \\ u & m & e \end{bmatrix} = \begin{bmatrix} a & b & c \\ u & m & e \\ 1 & 2 & 3 \end{bmatrix}$$

Proposition 3.4.3.

Let $A \in \mathbb{R}^{m \times n}$ then there exist elementary matrices E_1, E_2, \dots, E_k such that $rref(A) = E_1 E_2 \cdots E_k A$.

Proof: Gauss Jordan elimination consists of a sequence of k elementary row operations. Each row operation can be implemented by multiply the corresponding elementary matrix on the left. The Theorem follows. \square

Example 3.4.4. Just for fun let's see what happens if we multiply the elementary matrices on the right instead.

$$\begin{aligned}
 AE_{r_2+3r_1 \rightarrow r_2} &= \begin{bmatrix} a & b & c \\ 1 & 2 & 3 \\ u & m & e \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 3 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} a+3b & b & c \\ 1+6 & 2 & 3 \\ u+3m & m & e \end{bmatrix} \\
 AE_{7r_2 \rightarrow r_2} &= \begin{bmatrix} a & b & c \\ 1 & 2 & 3 \\ u & m & e \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 7 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} a & 7b & c \\ 1 & 14 & 3 \\ u & 7m & e \end{bmatrix} \\
 AE_{r_2 \rightarrow r_3} &= \begin{bmatrix} a & b & c \\ 1 & 2 & 3 \\ u & m & e \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} a & c & b \\ 1 & 3 & 2 \\ u & e & m \end{bmatrix}
 \end{aligned}$$

Curious, they generate column operations, we might call these elementary column operations. In our notation the row operations are more important.

3.5 invertible matrices

Definition 3.5.1.

Let $A \in \mathbb{R}^{n \times n}$. If there exists $B \in \mathbb{R}^{n \times n}$ such that $AB = I$ and $BA = I$ then we say that A is **invertible** and $A^{-1} = B$. Invertible matrices are also called **nonsingular**. If a matrix has no inverse then it is called a **noninvertible** or **singular** matrix.

Proposition 3.5.2.

Elementary matrices are invertible.

Proof: I list the inverse matrix for each below:

$$\begin{aligned}
 (E_{r_i+ar_j \rightarrow r_i})^{-1} &= [I : r_i - ar_j \rightarrow r_i] \\
 (E_{br_i \rightarrow r_i})^{-1} &= [I : \frac{1}{b}r_i \rightarrow r_i] \\
 (E_{r_i \leftrightarrow r_j})^{-1} &= [I : r_j \leftrightarrow r_i]
 \end{aligned}$$

I leave it to the reader to convince themselves that these are indeed inverse matrices. \square

Example 3.5.3. Let me illustrate the mechanics of the proof above, $E_{r_1+3r_2 \rightarrow r_1} = \begin{bmatrix} 1 & 3 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ and

$E_{r_1-3r_2 \rightarrow r_1} = \begin{bmatrix} 1 & -3 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ satisfy,

$$E_{r_1+3r_2 \rightarrow r_1} E_{r_1-3r_2 \rightarrow r_1} = \begin{bmatrix} 1 & 3 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & -3 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Likewise,

$$E_{r_1-3r_2 \rightarrow r_1} E_{r_1+3r_2 \rightarrow r_1} = \begin{bmatrix} 1 & -3 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 3 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Thus, $(E_{r_1+3r_2 \rightarrow r_1})^{-1} = E_{r_1-3r_2 \rightarrow r_1}$ just as we expected.

Theorem 3.5.4.

Let $A \in \mathbb{R}^{n \times n}$. The solution of $Ax = 0$ is unique iff A^{-1} exists.

Proof: (\Rightarrow) Suppose $Ax = 0$ has a unique solution. Observe $A0 = 0$ thus the only solution is the zero solution. Consequently, $rref[A|0] = [I|0]$. Moreover, by Proposition 3.4.3 there exist elementary matrices E_1, E_2, \dots, E_k such that $rref[A|0] = E_1 E_2 \dots E_k [A|0] = [I|0]$. Applying the concatenation Proposition 3.3.12 we find that $[E_1 E_2 \dots E_k A | E_1 E_2 \dots E_k 0] = [I|0]$ thus $E_1 E_2 \dots E_k A = I$.

It remains to show that $AE_1 E_2 \dots E_k = I$. Multiply $E_1 E_2 \dots E_k A = I$ on the left by E_1^{-1} followed by E_2^{-1} and so forth to obtain

$$E_k^{-1} \dots E_2^{-1} E_1^{-1} E_1 E_2 \dots E_k A = E_k^{-1} \dots E_2^{-1} E_1^{-1} I$$

this simplifies to

$$A = E_k^{-1} \dots E_2^{-1} E_1^{-1}.$$

Observe that

$$AE_1 E_2 \dots E_k = E_k^{-1} \dots E_2^{-1} E_1^{-1} E_1 E_2 \dots E_k = I.$$

We identify that $A^{-1} = E_1 E_2 \dots E_k$ thus A^{-1} exists.

(\Leftarrow) The converse proof is much easier. Suppose A^{-1} exists. If $Ax = 0$ then multiply by A^{-1} on the left, $A^{-1}Ax = A^{-1}0 \Rightarrow Ix = 0$ thus $x = 0$. \square

Proposition 3.5.5.

Let $A \in \mathbb{R}^{n \times n}$.

1. If $BA = I$ then $AB = I$.
2. If $AB = I$ then $BA = I$.

Proof of (1.): Suppose $BA = I$. If $Ax = 0$ then $BAX = B0$ hence $Ix = 0$. We have shown that $Ax = 0$ only has the trivial solution. Therefore, Theorem 3.5.4 shows us that A^{-1} exists. Multiply $BA = I$ on the left by A^{-1} to find $BAA^{-1} = IA^{-1}$ hence $B = A^{-1}$ and by definition it follows $AB = I$.

Proof of (2.): Suppose $AB = I$. If $Bx = 0$ then $ABx = A0$ hence $Ix = 0$. We have shown that $Bx = 0$ only has the trivial solution. Therefore, Theorem 3.5.4 shows us that B^{-1} exists. Multiply

$AB = I$ on the right by B^{-1} to find $ABB^{-1} = IB^{-1}$ hence $A = B^{-1}$ and by definition it follows $BA = I$. \square

Proposition 3.5.5 shows that we don't need to check both conditions $AB = I$ and $BA = I$. If either holds the other condition automatically follows.

Proposition 3.5.6.

If $A \in \mathbb{R}^{n \times n}$ is invertible then its inverse matrix is unique.

Proof: Suppose B, C are inverse matrices of A . It follows that $AB = BA = I$ and $AC = CA = I$ thus $AB = AC$. Multiply B on the left of $AB = AC$ to obtain $BAB = BAC$ hence $IB = IC \Rightarrow B = C$. \square

Example 3.5.7. In the case of a 2×2 matrix a nice formula to find the inverse is known:

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

It's not hard to show this formula works,

$$\begin{aligned} \frac{1}{ad - bc} \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix} &= \frac{1}{ad - bc} \begin{bmatrix} ad - bc & -ab + ab \\ cd - dc & -bc + da \end{bmatrix} \\ &= \frac{1}{ad - bc} \begin{bmatrix} ad - bc & 0 \\ 0 & ad - bc \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{aligned}$$

How did we know this formula? Can you derive it? To find the formula from first principles you could suppose there exists a matrix $B = \begin{bmatrix} x & y \\ z & w \end{bmatrix}$ such that $AB = I$. The resulting algebra would lead you to conclude $x = d/t, y = -b/t, z = -c/t, w = a/t$ where $t = ad - bc$. I leave this as an exercise for the reader.

There is a giant assumption made throughout the last example. What is it?

Example 3.5.8. Recall that a counterclockwise **rotation** by angle θ in the plane can be represented by a matrix $R(\theta) = \begin{bmatrix} \cos(\theta) & \sin(\theta) \\ -\sin(\theta) & \cos(\theta) \end{bmatrix}$. The inverse matrix corresponds to a rotation by angle $-\theta$

and (using the even/odd properties for cosine and sine) $R(-\theta) = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} = R(\theta)^{-1}$.

Notice that $R(0) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ thus $R(\theta)R(-\theta) = R(0) = I$. Rotations are very special invertible matrices, we shall see them again.

Theorem 3.5.9.

If $A, B \in \mathbb{R}^{n \times n}$ are invertible, $X, Y \in \mathbb{R}^{m \times n}$, $Z, W \in \mathbb{R}^{n \times m}$ and nonzero $c \in \mathbb{R}$ then

1. $(AB)^{-1} = B^{-1}A^{-1}$,
2. $(cA)^{-1} = \frac{1}{c}A^{-1}$,
3. $XA = YA$ implies $X = Y$,
4. $AZ = AW$ implies $Z = W$,

Proof: To prove (1.) simply notice that

$$(AB)B^{-1}A^{-1} = A(BB^{-1})A^{-1} = A(I)A^{-1} = AA^{-1} = I.$$

The proof of (2.) follows from the calculation below,

$$\left(\frac{1}{c}A^{-1}\right)cA = \frac{1}{c}cA^{-1}A = A^{-1}A = I.$$

To prove (3.) assume that $XA = YA$ and multiply both sides by A^{-1} on the right to obtain $XAA^{-1} = YAA^{-1}$ which reveals $XI = YI$ or simply $X = Y$. To prove (4.) multiply by A^{-1} on the left. \square

Remark 3.5.10.

The proofs just given were all matrix arguments. These contrast the component level proofs needed for 3.3.16. We could give component level proofs for the Theorem above but that is not necessary and those arguments would only obscure the point. I hope you gain your own sense of which type of argument is most appropriate as the course progresses.

We have a simple formula to calculate the inverse of a 2×2 matrix, but sadly no such simple formula exists for bigger matrices. There is a nice method to calculate A^{-1} (if it exists), but we do not have all the theory in place to discuss it at this juncture.

Proposition 3.5.11.

If $A_1, A_2, \dots, A_k \in \mathbb{R}^{n \times n}$ are invertible then

$$(A_1A_2 \cdots A_k)^{-1} = A_k^{-1}A_{k-1}^{-1} \cdots A_2^{-1}A_1^{-1}$$

Proof: Provided by you in the Problem Set. Your argument will involve induction on the index k . Notice you already have the cases $k = 1, 2$ from the arguments in this section. In particular, $k = 1$ is trivial and $k = 2$ is given by Theorem 3.5.11. \square

3.6 how to calculate the inverse of a matrix

We have not needed to solve more than one problem at a time before, however the problem of calculating an inverse amounts to precisely the problem of simultaneously solving several systems of equations at once. We thus begin with a bit of theory before attacking the inverse problem head-on.

3.6.1 concatenation for solving many systems at once

If we wish to solve $Ax = b_1$ and $Ax = b_2$ we use a concatenation trick to do both at once. In fact, we can do it for $k \in \mathbb{N}$ problems which share the same coefficient matrix but possibly differing inhomogeneous terms.

Proposition 3.6.1.

Let $A \in \mathbb{R}^{m \times n}$. Vectors v_1, v_2, \dots, v_k are solutions of $Av = b_i$ for $i = 1, 2, \dots, k$ iff $V = [v_1 | v_2 | \dots | v_k]$ solves $AV = B$ where $B = [b_1 | b_2 | \dots | b_k]$.

Proof: Let $A \in \mathbb{R}^{m \times n}$ and suppose $Av_i = b_i$ for $i = 1, 2, \dots, k$. Let $V = [v_1 | v_2 | \dots | v_k]$ and use the concatenation Proposition 3.3.12,

$$AV = A[v_1 | v_2 | \dots | v_k] = [Av_1 | Av_2 | \dots | Av_k] = [b_1 | b_2 | \dots | b_k] = B.$$

Conversely, suppose $AV = B$ where $V = [v_1 | v_2 | \dots | v_k]$ and $B = [b_1 | b_2 | \dots | b_k]$ then by Proposition 3.3.12 $AV = B$ implies $Av_i = b_i$ for each $i = 1, 2, \dots, k$. \square

Example 3.6.2. Solve the systems given below,

$$\begin{array}{rcl} x + y + z = 1 & & x + y + z = 1 \\ x - y + z = 0 & \text{and} & x - y + z = 1 \\ -x + z = 1 & & -x + z = 1 \end{array}$$

The systems above share the same coefficient matrix, however $b_1 = [1, 0, 1]^T$ whereas $b_2 = [1, 1, 1]^T$. We can solve both at once by making an extended augmented coefficient matrix $[A | b_1 | b_2]$

$$[A | b_1 | b_2] = \left[\begin{array}{ccc|c|c} 1 & 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & 0 & 1 \\ -1 & 0 & 1 & 1 & 1 \end{array} \right] \quad \text{rref}[A | b_1 | b_2] = \left[\begin{array}{ccc|c|c} 1 & 0 & 0 & -1/4 & 0 \\ 0 & 1 & 0 & 1/2 & 0 \\ 0 & 0 & 1 & 3/4 & 1 \end{array} \right]$$

We use Proposition 3.6.1 to conclude that

$$\begin{array}{rcl} x + y + z = 1 \\ x - y + z = 0 \\ -x + z = 1 \end{array} \quad \text{has solution } x = -1/4, y = 1/2, z = 3/4$$

$$\begin{array}{rcl} x + y + z = 1 \\ x - y + z = 1 \\ -x + z = 1 \end{array} \quad \text{has solution } x = 0, y = 0, z = 1.$$

3.6.2 the inverse-finding algorithm

PROBLEM: how should we calculate A^{-1} for a 3×3 matrix ?

Consider that the Proposition 3.6.1 gives us another way to look at the problem,

$$AA^{-1} = I \Leftrightarrow A[v_1|v_2|v_3] = I_3 = [e_1|e_2|e_3]$$

Where $v_i = \text{col}_i(A^{-1})$ and $e_1 = [0 \ 0 \ 0]^T$, $e_2 = [0 \ 1 \ 0]^T$, $e_3 = [0 \ 0 \ 1]^T$. We observe that the problem of finding A^{-1} for a 3×3 matrix amounts to solving three separate systems:

$$Av_1 = e_1, \quad Av_2 = e_2, \quad Av_3 = e_3$$

when we find the solutions then we can construct $A^{-1} = [v_1|v_2|v_3]$. Think about this, if A^{-1} exists then it is unique thus the solutions v_1, v_2, v_3 are likewise unique. Consequently, by Theorem 1.5.3,

$$\text{rref}[A|e_1] = [I|v_1], \quad \text{rref}[A|e_2] = [I|v_2], \quad \text{rref}[A|e_3] = [I|v_3].$$

Each of the systems above required the same sequence of elementary row operations to cause $A \mapsto I$. We can just as well do them at the same time in one big matrix calculation:

$$\text{rref}[A|e_1|e_2|e_3] = [I|v_1|v_2|v_3]$$

While this discuss was done for $n = 3$ we can just as well do the same for $n > 3$. This provides the proof for the first sentence of the theorem below. Theorem 1.5.3 together with the discussion above proves the second sentence.

Theorem 3.6.3.

If $A \in \mathbb{R}^{n \times n}$ is invertible then $\text{rref}[A|I] = [I|A^{-1}]$. Otherwise, A^{-1} **not** invertible iff $\text{rref}(A) \neq I$ iff $\text{rref}[A|I] \neq [I|B]$.

This is perhaps the most pragmatic theorem so far stated in these notes. This theorem tells us how and when we can find an inverse for a square matrix.

Example 3.6.4. Recall that in Example 1.2.7 we worked out the details of

$$\text{rref} \left[\begin{array}{ccc|ccc} 1 & 0 & 0 & 1 & 0 & 0 \\ 2 & 2 & 0 & 0 & 1 & 0 \\ 4 & 4 & 4 & 0 & 0 & 1 \end{array} \right] = \left[\begin{array}{ccc|ccc} 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & -1 & 1/2 & 0 \\ 0 & 0 & 1 & 0 & -1/2 & 1/4 \end{array} \right]$$

Thus,

$$\left[\begin{array}{ccc} 1 & 0 & 0 \\ 2 & 2 & 0 \\ 4 & 4 & 4 \end{array} \right]^{-1} = \left[\begin{array}{ccc} 1 & 0 & 0 \\ -1 & 1/2 & 0 \\ 0 & -1/2 & 1/4 \end{array} \right].$$

Example 3.6.5. *I omit the details of the Gaussian elimination,*

$$\text{rref} \left[\begin{array}{ccc|ccc} 1 & -1 & 0 & 1 & 0 & 0 \\ 1 & 0 & -1 & 0 & 1 & 0 \\ 6 & 2 & 3 & 0 & 0 & 1 \end{array} \right] = \left[\begin{array}{ccc|ccc} 1 & 0 & 0 & -2 & -3 & -1 \\ 0 & 1 & 0 & -3 & -3 & -1 \\ 0 & 0 & 1 & -2 & -4 & -1 \end{array} \right]$$

Thus,

$$\left[\begin{array}{ccc} 1 & -1 & 0 \\ 1 & 0 & -1 \\ 6 & 2 & 3 \end{array} \right]^{-1} = \left[\begin{array}{ccc} -2 & -3 & -1 \\ -3 & -3 & -1 \\ -2 & -4 & -1 \end{array} \right].$$

3.7 all your base are belong to us (e_i and E_{ij} that is)

Recall that we defined $e_i \in \mathbb{R}^n$ by $(e_i)_j = \delta_{ij}$. We call e_i the i -th standard basis vector. We proved in Proposition 2.2.8 that every vector in \mathbb{R}^n is a linear combination of e_1, e_2, \dots, e_n . We can define a standard basis for matrices of arbitrary size in much the same manner.

Definition 3.7.1.

The ij -th **standard basis matrix** for $\mathbb{R}^{m \times n}$ is denoted E_{ij} for $1 \leq i \leq m$ and $1 \leq j \leq n$. The matrix E_{ij} is zero in all entries except for the (i, j) -th slot where it has a 1. In other words, we define $(E_{ij})_{kl} = \delta_{ik}\delta_{jl}$.

Proposition 3.7.2.

Every matrix in $\mathbb{R}^{m \times n}$ is a linear combination of the E_{ij} where $1 \leq i \leq m$ and $1 \leq j \leq n$.

Proof: Let $A \in \mathbb{R}^{m \times n}$ then

$$\begin{aligned} A &= \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{mn} \end{bmatrix} \\ &= A_{11} \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & 0 \\ 0 & 0 & \cdots & 0 \end{bmatrix} + A_{12} \begin{bmatrix} 0 & 1 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & 0 \\ 0 & 0 & \cdots & 0 \end{bmatrix} + \cdots + A_{mn} \begin{bmatrix} 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & 0 \\ 0 & 0 & \cdots & 1 \end{bmatrix} \\ &= A_{11}E_{11} + A_{12}E_{12} + \cdots + A_{mn}E_{mn}. \end{aligned}$$

The calculation above follows from repeated mn -applications of the definition of matrix addition and another mn -applications of the definition of scalar multiplication of a matrix. We can restate

the final result in a more precise language,

$$A = \sum_{i=1}^m \sum_{j=1}^n A_{ij} E_{ij}.$$

As we claimed, any matrix can be written as a linear combination of the E_{ij} . \square

The term "basis" has a technical meaning which we will discuss at length in due time. For now, just think of it as part of the names of e_i and E_{ij} . These are the basic building blocks for matrix theory.

Example 3.7.3. Suppose $A \in \mathbb{R}^{m \times n}$ and $e_i \in \mathbb{R}^n$ is a standard basis vector,

$$(Ae_i)_j = \sum_{k=1}^n A_{jk}(e_i)_k = \sum_{k=1}^n A_{jk}\delta_{ik} = A_{ji}$$

Thus, $\boxed{[Ae_i] = \text{col}_i(A)}$. We find that multiplication of a matrix A by the standard basis e_i yields the i -th column of A .

Example 3.7.4. Suppose $A \in \mathbb{R}^{m \times n}$ and $e_i \in \mathbb{R}^{m \times 1}$ is a standard basis vector,

$$(e_i^T A)_j = \sum_{k=1}^n (e_i)_k A_{kj} = \sum_{k=1}^n \delta_{ik} A_{kj} = A_{ij}$$

Thus, $\boxed{[e_i^T A] = \text{row}_i(A)}$. We find multiplication of a matrix A by the transpose of standard basis e_i yields the i -th row of A .

Example 3.7.5. Again, suppose $e_i, e_j \in \mathbb{R}^n$ are standard basis vectors. The product $e_i^T e_j$ of the $1 \times n$ and $n \times 1$ matrices is just a 1×1 matrix which is just a number. In particular consider,

$$e_i^T e_j = \sum_{k=1}^n (e_i^T)_k (e_j)_k = \sum_{k=1}^n \delta_{ik} \delta_{jk} = \delta_{ij}$$

The product is zero unless the vectors are identical.

Example 3.7.6. Suppose $e_i \in \mathbb{R}^{m \times 1}$ and $e_j \in \mathbb{R}^n$. The product of the $m \times 1$ matrix e_i and the $1 \times n$ matrix e_j^T is an $m \times n$ matrix. In particular,

$$(e_i e_j^T)_{kl} = (e_i^T)_k (e_j)_l = \delta_{ik} \delta_{jl} = (E_{ij})_{kl}$$

Thus we can construct the standard basis matrices by multiplying the standard basis vectors; $E_{ij} = e_i e_j^T$.

Example 3.7.7. What about the matrix E_{ij} ? What can we say about multiplication by E_{ij} on the right of an arbitrary matrix? Let $A \in \mathbb{R}^{m \times n}$ and consider,

$$(AE_{ij})_{kl} = \sum_{p=1}^n A_{kp}(E_{ij})_{pl} = \sum_{p=1}^n A_{kp}\delta_{ip}\delta_{jl} = A_{ki}\delta_{jl}$$

Notice the matrix above has zero entries unless $j = l$ which means that the matrix is mostly zero except for the j -th column. We can select the j -th column by multiplying the above by e_j , using Examples 3.7.5 and 3.7.3,

$$(AE_{ij}e_j)_k = (Ae_ie_j^T e_j)_k = (Ae_i\delta_{jj})_k = (Ae_i)_k = (\text{col}_i(A))_k$$

This means,

$$AE_{ij} = \begin{bmatrix} & & & \text{column } j & & \\ 0 & 0 & \cdots & A_{1i} & \cdots & 0 \\ 0 & 0 & \cdots & A_{2i} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & A_{mi} & \cdots & 0 \end{bmatrix}$$

Right multiplication of matrix A by E_{ij} moves the i -th column of A to the j -th column of AE_{ij} and all other entries are zero. It turns out that left multiplication by E_{ij} moves the j -th row of A to the i -th row and sets all other entries to zero.

Example 3.7.8. Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ consider multiplication by E_{12} ,

$$AE_{12} = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 3 \end{bmatrix} = \begin{bmatrix} 0 & | & \text{col}_1(A) \end{bmatrix}$$

Which agrees with our general abstract calculation in the previous example. Next consider,

$$E_{12}A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} = \begin{bmatrix} 3 & 4 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} \text{row}_2(A) \\ 0 \end{bmatrix}.$$

Example 3.7.9. Calculate the product of E_{ij} and E_{kl} .

$$(E_{ij}E_{kl})_{mn} = \sum_p (E_{ij})_{mp}(E_{kl})_{pn} = \sum_p \delta_{im}\delta_{jp}\delta_{kp}\delta_{ln} = \delta_{im}\delta_{jk}\delta_{ln}$$

For example,

$$(E_{12}E_{34})_{mn} = \delta_{1m}\delta_{23}\delta_{4n} = 0.$$

In order for the product to be nontrivial we must have $j = k$,

$$(E_{12}E_{24})_{mn} = \delta_{1m}\delta_{22}\delta_{4n} = \delta_{1m}\delta_{4n} = (E_{14})_{mn}.$$

We can make the same identification in the general calculation,

$$(E_{ij}E_{kl})_{mn} = \delta_{jk}(E_{il})_{mn}.$$

Since the above holds for all m, n ,

$$E_{ij}E_{kl} = \delta_{jk}E_{il}$$

this is at times a very nice formula to know about.

Remark 3.7.10.

You may find the general examples in this portion of the notes a bit too much to follow. If that is the case then don't despair. Focus on mastering the numerical examples to begin with then come back to this section later. These examples are actually not that hard, you just have to get used to index calculations. The proofs in these examples are much longer if written without the benefit of index notation. I was disappointed your text fails to use the index notation in it's full power. The text deliberately uses $+\dots$ rather than \sum . I will use both languages.

Example 3.7.11. Let $A \in \mathbb{R}^{m \times n}$ and suppose $e_i \in \mathbb{R}^{m \times 1}$ and $e_j \in \mathbb{R}^n$. Consider,

$$(e_i)^T A e_j = \sum_{k=1}^m ((e_i)^T)_k (A e_j)_k = \sum_{k=1}^m \delta_{ik} (A e_j)_k = (A e_j)_i = A_{ij}$$

This is a useful observation. If we wish to select the (i, j) -entry of the matrix A then we can use the following simple formula,

$$A_{ij} = (e_i)^T A e_j$$

This is analogous to the idea of using dot-products to select particular components of vectors in analytic geometry; (reverting to calculus III notation for a moment) recall that to find v_1 of \vec{v} we learned that the dot product by $\hat{i} = \langle 1, 0, 0 \rangle$ selects the first components $v_1 = \vec{v} \cdot \hat{i}$. The following theorem is simply a summary of our results for this section.

Theorem 3.7.12.

Assume $A \in \mathbb{R}^{m \times n}$ and $v \in \mathbb{R}^n$ and define $(E_{ij})_{kl} = \delta_{ik}\delta_{jl}$ and $(e_i)_j = \delta_{ij}$ as we previously discussed,

$$v = \sum_{i=1}^n v_i e_i \quad A = \sum_{i=1}^m \sum_{j=1}^n A_{ij} E_{ij}.$$

$$[e_i^T A] = \text{row}_i(A) \quad [A e_j] = \text{col}_j(A) \quad A_{ij} = (e_i)^T A e_j$$

$$E_{ij}E_{kl} = \delta_{jk}E_{il} \quad E_{ij} = e_i e_j^T \quad e_i^T e_j = \delta_{ij}$$

3.8 block matrices

If you look at most undergraduate linear algebra texts they will not bother to even attempt much of a proof that block-multiplication holds in general. I will foolishly attempt it here. However, I'm going to cheat a little and employ uber-sneaky physics notation. The Einstein summation convention states that if an index is repeated then it is assumed to be summed over its values. This means that the letters used for particular indices are reserved. If i, j, k are used to denote components of a spatial vector then you cannot use them for a spacetime vector at the same time. A typical notation in physics would be that v^j is a vector in xyz -space whereas v^μ is a vector in $txyz$ -spacetime. A spacetime vector could be written as a sum of space components and a time component; $v = v^\mu e_\mu = v^0 e_0 + v^1 e_1 + v^2 e_2 + v^3 e_3 = v^0 e_0 + v^j e_j$. This is not the sort of language we use in mathematics. For us notation is usually not reserved. Anyway, cultural commentary aside, if we were to use Einstein-type notation in linear algebra then we would likely omit sums as follows:

$$v = \sum_i v_i e_i \longrightarrow v = v_i e_i$$

$$A = \sum_{ij} A_{ij} E_{ij} \longrightarrow A = A_{ij} E_{ij}$$

We wish to partition a matrices A and B into 4 parts, use indices M, N which split into subindices m, μ and n, ν respectively. In this notation there are 4 different types of pairs possible:

$$A = [A_{MN}] = \left[\begin{array}{c|c} A_{mn} & A_{m\nu} \\ \hline A_{\mu n} & A_{\mu\nu} \end{array} \right] \quad B = [B_{NJ}] = \left[\begin{array}{c|c} B_{nj} & B_{n\gamma} \\ \hline B_{\mu j} & B_{\mu\gamma} \end{array} \right]$$

Then the sum over M, N breaks into 2 cases,

$$A_{MN} B_{NJ} = A_{Mn} B_{nJ} + A_{M\nu} B_{\nu J}$$

But, then there are 4 different types of M, J pairs,

$$[AB]_{mj} = A_{mN} B_{NJ} = A_{mn} B_{nj} + A_{m\nu} B_{\nu j}$$

$$[AB]_{m\gamma} = A_{mN} B_{N\gamma} = A_{mn} B_{n\gamma} + A_{m\nu} B_{\nu\gamma}$$

$$[AB]_{\mu j} = A_{\mu N} B_{NJ} = A_{\mu n} B_{nj} + A_{\mu\nu} B_{\nu j}$$

$$[AB]_{\mu\gamma} = A_{\mu N} B_{N\gamma} = A_{\mu n} B_{n\gamma} + A_{\mu\nu} B_{\nu\gamma}$$

Let me summarize,

$$\left[\begin{array}{c|c} A_{mn} & A_{m\nu} \\ \hline A_{\mu n} & A_{\mu\nu} \end{array} \right] \left[\begin{array}{c|c} B_{nj} & B_{n\gamma} \\ \hline B_{\mu j} & B_{\mu\gamma} \end{array} \right] = \left[\begin{array}{c|c} [A_{mn}][B_{nj}] + [A_{m\nu}][B_{\nu j}] & [A_{mn}][B_{n\gamma}] + [A_{m\nu}][B_{\nu\gamma}] \\ \hline [A_{\mu n}][B_{nj}] + [A_{\mu\nu}][B_{\nu j}] & [A_{\mu n}][B_{n\gamma}] + [A_{\mu\nu}][B_{\nu\gamma}] \end{array} \right]$$

Let me again summarize, but this time I'll drop the annoying indices:

Theorem 3.8.1. *block multiplication.*

Suppose $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times p}$ such that both A and B are partitioned as follows:

$$A = \left[\begin{array}{c|c} A_{11} & A_{12} \\ \hline A_{21} & A_{22} \end{array} \right] \quad \text{and} \quad B = \left[\begin{array}{c|c} B_{11} & B_{12} \\ \hline B_{21} & B_{22} \end{array} \right]$$

where A_{11} is an $m_1 \times n_1$ block, A_{12} is an $m_1 \times n_2$ block, A_{21} is an $m_2 \times n_1$ block and A_{22} is an $m_2 \times n_2$ block. Likewise, $B_{n_k p_k}$ is an $n_k \times p_k$ block for $k = 1, 2$. We insist that $m_1 + m_2 = m$ and $n_1 + n_2 = n$. If the partitions are compatible as described above then we may multiply A and B by multiplying the blocks as if they were scalars and we were computing the product of 2×2 matrices:

$$\left[\begin{array}{c|c} A_{11} & A_{12} \\ \hline A_{21} & A_{22} \end{array} \right] \left[\begin{array}{c|c} B_{11} & B_{12} \\ \hline B_{21} & B_{22} \end{array} \right] = \left[\begin{array}{c|c} A_{11}B_{11} + A_{12}B_{21} & A_{11}B_{12} + A_{12}B_{22} \\ \hline A_{21}B_{11} + A_{22}B_{21} & A_{21}B_{12} + A_{22}B_{22} \end{array} \right].$$

To give a careful proof we'd just need to write out many sums and define the partition with care from the outset of the proof. In any event, notice that once you have this partition you can apply it twice to build block-multiplication rules for matrices with more blocks. The basic idea remains the same: you can parse two matrices into matching partitions then the matrix multiplication follows a pattern which is as if the blocks were scalars. However, the blocks are not scalars so the multiplication of the blocks is nonabelian. For example,

$$AB = \left[\begin{array}{c|c} A_{11} & A_{12} \\ \hline A_{21} & A_{22} \\ \hline A_{31} & A_{32} \end{array} \right] \left[\begin{array}{c|c} B_{11} & B_{12} \\ \hline B_{21} & B_{22} \end{array} \right] = \left[\begin{array}{c|c} A_{11}B_{11} + A_{12}B_{21} & A_{11}B_{12} + A_{12}B_{22} \\ \hline A_{21}B_{11} + A_{22}B_{21} & A_{21}B_{12} + A_{22}B_{22} \\ \hline A_{31}B_{11} + A_{32}B_{21} & A_{31}B_{12} + A_{32}B_{22} \end{array} \right].$$

where if the partitions of A and B are compatible it follows that the block-multiplications on the RHS are all well-defined.

Example 3.8.2. Let $R(\theta) = \begin{bmatrix} \cos(\theta) & \sin(\theta) \\ -\sin(\theta) & \cos(\theta) \end{bmatrix}$ and $B(\gamma) = \begin{bmatrix} \cosh(\gamma) & \sinh(\gamma) \\ \sinh(\gamma) & \cosh(\gamma) \end{bmatrix}$. Furthermore construct 4×4 matrices Λ_1 and Λ_2 as follows:

$$\Lambda_1 = \left[\begin{array}{c|c} B(\gamma_1) & 0 \\ \hline 0 & R(\theta_1) \end{array} \right] \quad \Lambda_2 = \left[\begin{array}{c|c} B(\gamma_2) & 0 \\ \hline 0 & R(\theta_2) \end{array} \right]$$

Multiply Λ_1 and Λ_2 via block multiplication:

$$\begin{aligned} \Lambda_1 \Lambda_2 &= \left[\begin{array}{c|c} B(\gamma_1) & 0 \\ \hline 0 & R(\theta_1) \end{array} \right] \left[\begin{array}{c|c} B(\gamma_2) & 0 \\ \hline 0 & R(\theta_2) \end{array} \right] \\ &= \left[\begin{array}{c|c} B(\gamma_1)B(\gamma_2) + 0 & 0 + 0 \\ \hline 0 + 0 & 0 + R(\theta_1)R(\theta_2) \end{array} \right] \\ &= \left[\begin{array}{c|c} B(\gamma_1 + \gamma_2) & 0 \\ \hline 0 & R(\theta_1 + \theta_2) \end{array} \right]. \end{aligned}$$

The last calculation is actually a few lines in detail, if you know the adding angles formulas for cosine, sine, cosh and sinh it's easy. If $\theta = 0$ and $\gamma \neq 0$ then Λ would represent a **velocity boost** on spacetime. Since it mixes time and the first coordinate the velocity is along the x -coordinate. On the other hand, if $\theta \neq 0$ and $\gamma = 0$ then Λ gives a **rotation** in the yz spatial coordinates in space time. If both parameters are nonzero then we can say that Λ is a **Lorentz transformation** on spacetime. Of course there is more to say here, perhaps we could offer a course in special relativity if enough students were interested in concert.

Example 3.8.3. Problem: Suppose M is a square matrix with submatrices $A, B, C, 0$. What conditions should we insist on for $M = \left[\begin{array}{c|c} A & B \\ \hline 0 & C \end{array} \right]$ to be invertible.

Solution: I propose we partition the potential inverse matrix $M^{-1} = \left[\begin{array}{c|c} D & E \\ \hline F & G \end{array} \right]$. We seek to find conditions on A, B, C such that there exist D, E, F, G and $MM^{-1} = I$. Each block of the equation $MM^{-1} = I$ gives us a separate submatrix equation:

$$MM^{-1} = \left[\begin{array}{c|c} A & B \\ \hline 0 & C \end{array} \right] \left[\begin{array}{c|c} D & E \\ \hline F & G \end{array} \right] = \left[\begin{array}{c|c} AD + BF & AE + BG \\ \hline 0D + CF & 0E + CG \end{array} \right] = \left[\begin{array}{c|c} I & 0 \\ \hline 0 & I \end{array} \right]$$

We must solve simultaneously the following:

$$(1.) AD + BF = I, \quad (2.) AE + BG = 0, \quad (3.) CF = 0, \quad (4.) CG = I$$

If C^{-1} exists then $G = C^{-1}$ from (4.). Moreover, (3.) then yields $F = C^{-1}0 = 0$. Our problem thus reduces to (1.) and (2.) which after substituting $F = 0$ and $G = C^{-1}$ yield

$$(1.) AD = I, \quad (2.) AE + BC^{-1} = 0.$$

Equation (1.) says $D = A^{-1}$. Finally, let's solve (2.) for E ,

$$E = -A^{-1}BC^{-1}.$$

Let's summarize the calculation we just worked through. IF A, C are invertible then the matrix $M = \left[\begin{array}{c|c} A & B \\ \hline 0 & C \end{array} \right]$ is invertible with inverse

$$M^{-1} = \left[\begin{array}{c|c} A^{-1} & -A^{-1}BC^{-1} \\ \hline 0 & C^{-1} \end{array} \right].$$

Consider the case that M is a 2×2 matrix and $A, B, C \in \mathbb{R}$. Then the condition of invertibility reduces to the simple conditions $A, C \neq 0$ and $-A^{-1}BC^{-1} = \frac{-B}{AC}$ we find the formula:

$$M^{-1} = \left[\begin{array}{c|c} \frac{1}{A} & \frac{-B}{AC} \\ \hline 0 & \frac{1}{C} \end{array} \right] = \frac{1}{AC} \left[\begin{array}{c|c} C & -B \\ \hline 0 & A \end{array} \right].$$

This is of course the formula for the 2×2 matrix in this special case where $M_{21} = 0$.

Of course the real utility of formulas like those in the last example is that they work for partitions of arbitrary size. If we can find a block of zeros somewhere in the matrix then we may reduce the size of the problem. The time for a computer calculation is largely based on some power of the size of the matrix. For example, if the calculation in question takes n^2 steps then parsing the matrix into 3 nonzero blocks which are $n/2 \times n/2$ would result in something like $[n/2]^2 + [n/2]^2 + [n/2]^2 = \frac{3}{4}n^2$ steps. If the calculation took on order n^3 computer operations (flops) then my toy example of 3 blocks would reduce to something like $[n/2]^3 + [n/2]^3 + [n/2]^3 = \frac{3}{8}n^3$ flops. A savings of more than 60% of computer time. If the calculation was typically order n^4 for an $n \times n$ matrix then the saving is even more dramatic. If the calculation is a determinant then the cofactor formula depends on the factorial of the size of the matrix. Try to compare $10!+10!$ verses say $20!$. Hope your calculator has a big display:

$$10! = 3628800 \Rightarrow 10! + 10! = 7257600 \quad \text{or} \quad 20! = 2432902008176640000.$$

Perhaps you can start to appreciate why numerical linear algebra software packages often use algorithms which make use of block matrices to streamline large matrix calculations. If you are very interested in this sort of topic you might strike up a conversation with Dr. Van Voorhis. I suspect he knows useful things about this type of mathematical inquiry.

Finally, I would comment that breaking a matrix into blocks is basically the bread and butter of quantum mechanics. One attempts to find a basis of state vectors which makes the Hamiltonian into a block-diagonal matrix. Each block corresponds to a certain set of statevectors sharing a common energy. The goal of representation theory in physics is basically to break down matrices into blocks with nice physical meanings. On the other hand, abstract algebraists also use blocks to rip apart a matrix into it's most basic form. For linear algebraists¹, the so-called Jordan form is full of blocks. Wherever reduction of a linear system into smaller subsystems is of interest there will be blocks.

3.9 matrices with notable properties

In this section we learn about a few special types of matrices.

3.9.1 symmetric and antisymmetric matrices

Definition 3.9.1.

Let $A \in \mathbb{R}^{n \times n}$. We say A is **symmetric** iff $A^T = A$. We say A is **antisymmetric** iff $A^T = -A$.

At the level of components, $A^T = A$ gives $A_{ij} = A_{ji}$ for all i, j . Whereas, $A^T = -A$ gives $A_{ij} = -A_{ji}$ for all i, j . I should mention **skew-symmetric** is another word for antisymmetric. In physics, second rank (anti)symmetric tensors correspond to (anti)symmetric matrices. In electromagnetism,

¹mostly dead by now sad to say.

the electromagnetic field tensor has components which can be written as an antisymmetric 4×4 matrix. In classical mechanics, a solid propensity to spin in various directions is described by the inertia tensor which is symmetric. The energy-momentum tensor from electrodynamics is also symmetric. Matrices are everywhere if look for them.

Example 3.9.2. *Some matrices are symmetric:*

$$I, O, E_{ii}, \begin{bmatrix} 1 & 2 \\ 2 & 0 \end{bmatrix}$$

Some matrices are antisymmetric:

$$O, \begin{bmatrix} 0 & 2 \\ -2 & 0 \end{bmatrix}$$

Only 0 is both symmetric and antisymmetric (can you prove it?). Many other matrices are neither symmetric nor antisymmetric:

$$e_i, E_{i,i+1}, \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$$

I assumed $n > 1$ so that e_i is a column vector which is not square.

Proposition 3.9.3.

Let $A, B \in \mathbb{R}^{n \times n}$ and $c \in \mathbb{R}$ then

1. $(A^T)^T = A$
2. $(AB)^T = B^T A^T$ socks-shoes property for transpose of product
3. $(cA)^T = cA^T$
4. $(A + B)^T = A^T + B^T$
5. $(A^T)^{-1} = (A^{-1})^T$.

Proof: To prove (1.) simply note that $((A^T)^T)_{ij} = (A^T)_{ji} = A_{ij}$ for all i, j . Proof of (2.) is left to the reader. Proof of (3.) and (4.) is simple enough,

$$((A + cB)^T)_{ij} = (A + cB)_{ji} = A_{ji} + cB_{ji} = (A^T)_{ij} + ((cB)^T)_{ij}$$

for all i, j . Proof of (5.) is again left to the reader². \square

²I wouldn't be surprised if I was asked to prove (2.) or (5.) on a quiz or test.

Proposition 3.9.4.

All square matrices are formed by the sum of a symmetric and antisymmetric matrix.

Proof: Let $A \in \mathbb{R}^{n \times n}$. Utilizing Proposition 3.9.3 we find

$$\left(\frac{1}{2}(A + A^T) \right)^T = \frac{1}{2}(A^T + (A^T)^T) = \frac{1}{2}(A^T + A) = \frac{1}{2}(A + A^T)$$

thus $\frac{1}{2}(A + A^T)$ is a symmetric matrix. Likewise,

$$\left(\frac{1}{2}(A - A^T) \right)^T = \frac{1}{2}(A^T - (A^T)^T) = \frac{1}{2}(A^T - A) = -\frac{1}{2}(A - A^T)$$

thus $\frac{1}{2}(A - A^T)$ is an antisymmetric matrix. Finally, note the identity below:

$$A = \frac{1}{2}(A + A^T) + \frac{1}{2}(A - A^T)$$

The theorem follows. \square

The proof that any function on \mathbb{R} is the sum of an even and odd function uses the same trick.

Example 3.9.5. *The proof of the Proposition above shows us how to break up the matrix into its symmetric and antisymmetric pieces:*

$$\begin{aligned} \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} &= \frac{1}{2} \left(\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} + \begin{bmatrix} 1 & 3 \\ 2 & 4 \end{bmatrix} \right) + \frac{1}{2} \left(\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} - \begin{bmatrix} 1 & 3 \\ 2 & 4 \end{bmatrix} \right) \\ &= \begin{bmatrix} 1 & 5/2 \\ 5/2 & 4 \end{bmatrix} + \begin{bmatrix} 0 & -1/2 \\ 1/2 & 0 \end{bmatrix}. \end{aligned}$$

Example 3.9.6. *What are the symmetric and antisymmetric parts of the standard basis E_{ij} in $\mathbb{R}^{n \times n}$? Here the answer depends on the choice of i, j . Note that $(E_{ij})^T = E_{ji}$ for all i, j . Suppose $i = j$ then $E_{ij} = E_{ii}$ is clearly symmetric, thus there is no antisymmetric part. If $i \neq j$ we use the standard trick,*

$$E_{ij} = \frac{1}{2}(E_{ij} + E_{ji}) + \frac{1}{2}(E_{ij} - E_{ji})$$

where $\frac{1}{2}(E_{ij} + E_{ji})$ is the symmetric part of E_{ij} and $\frac{1}{2}(E_{ij} - E_{ji})$ is the antisymmetric part of E_{ij} .

Proposition 3.9.7.

Let $A \in \mathbb{R}^{m \times n}$ then $A^T A$ is symmetric.

Proof: Proposition 3.9.3 yields $(A^T A)^T = A^T (A^T)^T = A^T A$. Thus $A^T A$ is symmetric. \square

3.9.2 exponent laws for matrices

The power of a matrix is defined in the natural way. Notice we need for A to be square in order for the product AA to be defined.

Definition 3.9.8.

Let $A \in \mathbb{R}^{n \times n}$. We define $A^0 = I$, $A^1 = A$ and $A^m = AA^{m-1}$ for all $m \geq 1$. If A is invertible then $A^{-p} = (A^{-1})^p$.

As you would expect, $A^3 = AA^2 = AAA$.

Proposition 3.9.9.

Let $A, B \in \mathbb{R}^{n \times n}$ and $p, q \in \mathbb{N} \cup \{0\}$

1. $(A^p)^q = A^{pq}$.
2. $A^p A^q = A^{p+q}$.
3. If A is invertible, $(A^{-1})^{-1} = A$.

Proof: left to reader. \square

You should notice that $(AB)^p \neq A^p B^p$ for matrices. Instead,

$$(AB)^2 = ABAB, \quad (AB)^3 = ABABAB, \text{ etc...}$$

This means the binomial theorem will not hold for matrices. For example,

$$(A + B)^2 = (A + B)(A + B) = A(A + B) + B(A + B) = AA + AB + BA + BB$$

hence $(A + B)^2 \neq A^2 + 2AB + B^2$ as the matrix product is not generally commutative. If we have A and B commute then $AB = BA$ and we can prove that $(AB)^p = A^p B^p$ and the binomial theorem holds true.

Proposition 3.9.10.

If A is symmetric then A^k is symmetric for all $k \in \mathbb{N}$.

Proof: Suppose $A^T = A$. Proceed inductively. Clearly $k = 1$ holds true since $A^1 = A$. Assume inductively that A^k is symmetric.

$$\begin{aligned} (A^{k+1})^T &= (AA^k)^T && \text{defn. of matrix exponents,} \\ &= (A^k)^T A^T && \text{socks-shoes prop. of transpose,} \\ &= A^k A && \text{using induction hypothesis.} \\ &= A^{k+1} && \text{defn. of matrix exponents,} \end{aligned}$$

thus by proof by mathematical induction A^k is symmetric for all $k \in \mathbb{N}$. \square

There are many other fun identities about symmetric and invertible matrices. I'll probably put a few in the Problem Set since they make nice easy proof problems.

3.9.3 diagonal and triangular matrices

Definition 3.9.11.

Let $A \in \mathbb{R}^{m \times n}$. If $A_{ij} = 0$ for all i, j such that $i \neq j$ then A is called a **diagonal** matrix. If A has components $A_{ij} = 0$ for all i, j such that $i \leq j$ then we call A a **upper triangular** matrix. If A has components $A_{ij} = 0$ for all i, j such that $i \geq j$ then we call A a **lower triangular** matrix.

Example 3.9.12. Let me illustrate a generic example of each case for 3×3 matrices:

$$\begin{bmatrix} A_{11} & 0 & 0 \\ 0 & A_{22} & 0 \\ 0 & 0 & A_{33} \end{bmatrix} \quad \begin{bmatrix} A_{11} & A_{12} & A_{13} \\ 0 & A_{22} & A_{23} \\ 0 & 0 & A_{33} \end{bmatrix} \quad \begin{bmatrix} A_{11} & 0 & 0 \\ A_{21} & A_{22} & 0 \\ A_{31} & A_{32} & A_{33} \end{bmatrix}$$

As you can see the diagonal matrix only has nontrivial entries on the diagonal, and the names lower triangular and upper triangular are likewise natural.

If an upper triangular matrix has zeros on the diagonal then it is said to be **strictly upper triangular**. Likewise, if a lower triangular matrix has zeros on the diagonal then it is said to be **strictly lower triangular**. Obviously any matrix can be written as a sum of a diagonal and strictly upper and strictly lower matrix,

$$\begin{aligned} A &= \sum_{i,j} A_{ij} E_{ij} \\ &= \sum_i A_{ii} E_{ii} + \sum_{i < j} A_{ij} E_{ij} + \sum_{i > j} A_{ij} E_{ij} \end{aligned}$$

There is an algorithm called *LU*-factorization which for many matrices A finds a lower triangular matrix L and an upper triangular matrix U such that $A = LU$. It is one of several factorization schemes which is computationally advantageous for large systems. There are many many ways to solve a system, but some are faster methods. Algorithmics is the study of which method is optimal.

Proposition 3.9.13.

Let $A, B \in \mathbb{R}^{n \times n}$.

1. If A, B are upper diagonal then AB is diagonal.
2. If A, B are upper triangular then AB is upper triangular.
3. If A, B are lower triangular then AB is lower triangular.

Proof of (1.): Suppose A and B are diagonal. It follows there exist a_i, b_j such that $A = \sum_i a_i E_{ii}$ and $B = \sum_j b_j E_{jj}$. Calculate,

$$\begin{aligned}
 AB &= \sum_i a_i E_{ii} \sum_j b_j E_{jj} \\
 &= \sum_i \sum_j a_i b_j E_{ii} E_{jj} \\
 &= \sum_i \sum_j a_i b_j \delta_{ij} E_{ij} \\
 &= \sum_i a_i b_i E_{ii}
 \end{aligned}$$

thus the product matrix AB is also diagonal and we find that the diagonal of the product AB is just the product of the corresponding diagonals of A and B .

Proof of (2.): Suppose A and B are upper diagonal. It follows there exist A_{ij}, B_{ij} such that $A = \sum_{i \leq j} A_{ij} E_{ij}$ and $B = \sum_{k \leq l} B_{kl} E_{kl}$. Calculate,

$$\begin{aligned}
 AB &= \sum_{i \leq j} A_{ij} E_{ij} \sum_{k \leq l} B_{kl} E_{kl} \\
 &= \sum_{i \leq j} \sum_{k \leq l} A_{ij} B_{kl} E_{ij} E_{kl} \\
 &= \sum_{i \leq j} \sum_{k \leq l} A_{ij} B_{kl} \delta_{jk} E_{il} \\
 &= \sum_{i \leq j} \sum_{j \leq l} A_{ij} B_{jl} E_{il}
 \end{aligned}$$

Notice that every term in the sum above has $i \leq j$ and $j \leq l$ hence $i \leq l$. It follows the product is upper triangular since it is a sum of upper triangular matrices. The proof of (3.) is similar. \square .

3.10 LU factorization

In this section we will use elementary matrices which correspond to the forward pass of the Gaussian elimination to factor matrices into a pair of simpler matrices; our goal is to factor a matrix A into a lower triangular matrix L and an upper triangular matrix U ; we hope to find $A = LU$. In the abstract the idea for the factorization simply comes from thinking about how we calculate $\text{ref}(A)$. To obtain $\text{ref}(A)$ one begins with A and then performs row operations until we have reduced the matrix to the form $\text{ref}(A)$. Each row operation can be implemented by a corresponding left multiplication by an elementary matrix so symbolically we can summarize the forward pass by the following equation:

$$\boxed{E_k E_{k-1} \cdots E_3 E_2 E_1 A = \text{ref}(A)}$$

The matrix $\text{ref}(A)$ has pivot positions with a nonzero number \star in each such entry. Moreover, by construction there are no nonzero entries below the pivot positions hence $\text{ref}(A)$ is an upper triangular matrix. Generically the pattern is something like

$$\text{ref}(A) = \begin{bmatrix} \star & * & * & * \\ 0 & 0 & \star & * \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

where again $\star \neq 0$ but $*$'s can be anything. Solve the boxed equation for A ,

$$\boxed{A = \underbrace{E_1^{-1} E_2^{-1} E_3^{-1} \cdots E_{k-1}^{-1} E_k^{-1}}_{\text{maybe } L ?} \underbrace{\text{ref}(A)}_U}$$

The inverse of elementary matrices are easily obtained and the product of those matrices is easily assembled if we just keep track of the row reduction to produce $\text{ref}(A)$. Let's see how this works out for a few examples.

Example 3.10.1. Let me modify the row reduction we studied in Example 1.2.3,

$$A = \begin{bmatrix} 1 & -1 & 1 \\ 3 & -3 & 0 \\ 2 & -2 & -3 \end{bmatrix} \xrightarrow[\text{(this is } E_1)]{r_2 - 3r_1 \rightarrow r_2} \begin{bmatrix} 1 & -1 & 1 \\ 0 & 0 & -3 \\ 2 & -2 & -3 \end{bmatrix} \xrightarrow[\text{(this is } E_2)]{r_3 - 2r_1 \rightarrow r_3}$$

$$\begin{bmatrix} 1 & -1 & 1 \\ 0 & 0 & -3 \\ 0 & 0 & -5 \end{bmatrix} \xrightarrow[\text{(this is } E_3)]{r_3 - \frac{5}{3}r_2 \rightarrow r_3} \begin{bmatrix} 1 & -1 & 1 \\ 0 & 0 & -3 \\ 0 & 0 & 0 \end{bmatrix} = U$$

Recall that elementary matrices are obtained by performing the corresponding operations on the identity matrix. We have $U = E_3E_2E_1A$, in particular $E_1 = \{I : r_2 - 3r_1 \rightarrow r_2\}$. Observe that $A = E_1^{-1}E_2^{-1}E_3^{-1}U$ and calculate the product $E_1^{-1}E_2^{-1}E_3^{-1}$ as follows:³

$$I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \xrightarrow[\text{(this is } E_3^{-1})]{r_3 + \frac{5}{3}r_2 \rightarrow r_3} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & \frac{5}{3} & 1 \end{bmatrix} \xrightarrow{r_3 + 2r_1 \rightarrow r_3}$$

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 2 & \frac{5}{3} & 1 \end{bmatrix} \xrightarrow{r_2 + 3r_1 \rightarrow r_2} \begin{bmatrix} 1 & 0 & 0 \\ 3 & 1 & 0 \\ 2 & \frac{5}{3} & 1 \end{bmatrix} = L$$

At the end of this section I'll return to this example once more and streamline the calculation. I'm trying to explain why the later algorithm works in detail to begin. The reason we are doing this and not just the algorithm at the end of the section is that you still need to think more about elementary matrices and this is a pretty good mathematical laboratory to test things out. We find A is factored into a lower and upper triangular matrix:

$$A = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 3 & 1 & 0 \\ 2 & \frac{5}{3} & 1 \end{bmatrix}}_L \underbrace{\begin{bmatrix} 1 & -1 & 1 \\ 0 & 0 & -3 \\ 0 & 0 & 0 \end{bmatrix}}_U.$$

Example 3.10.2. Find an LU-decomposition of A given below (if possible).

$$A = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 2 & 3 & 4 & 5 \\ 2 & 2 & 2 & 2 \end{bmatrix} \xrightarrow{r_2 - 2r_1 \rightarrow r_2} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & 2 & 3 \\ 2 & 2 & 2 & 2 \end{bmatrix} \xrightarrow{r_3 - 2r_1 \rightarrow r_3}$$

$$\begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & 2 & 3 \\ 0 & 0 & 0 & 0 \end{bmatrix} = U$$

³note the E_3^{-1} goes first since $E_1^{-1}E_2^{-1}E_3^{-1} = E_1^{-1}E_2^{-1}E_3^{-1}I$, we have to multiply I on left to interpret elementary matrices as row operations, if I was to multiply on the right then it does column operations instead... anyway, this is how to quickly calculate the product of elementary matrices. If for some reason this is confusing then perhaps you might try writing down the 3×3 matrices for each elementary matrix $E_1^{-1}, E_2^{-1}, E_3^{-1}$ then explicitly multiply these out. I prefer to do a few row operations on the identity matrix instead

In this example, we have $U = E_2 E_1 A$ hence $A = E_1^{-1} E_2^{-1} U$ and we can calculate the product $E_1^{-1} E_2^{-1}$ as follows:

$$I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \xrightarrow{r_3 + 2r_1 \rightarrow r_3} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix} \xrightarrow{r_2 + 2r_1 \rightarrow r_2} \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix} = L$$

We find A factors as follows:

$$A = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix}}_L \underbrace{\begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & 2 & 3 \\ 0 & 0 & 0 & 0 \end{bmatrix}}_U$$

Notice that in both of the last examples the L was really obtained by taking the identity matrix and inserting a couple numbers below the diagonal. In both cases those numbers were linked to the row operations performed in the forward pass. Keep this in mind for the end of the section.

If we can reduce A to an upper triangular matrix U using only row additions as in the last two examples then it seems entirely plausible that we will be able to find an LU -decomposition for A . However, in the next example we'll see that row-interchanges spoils the simplicity of the method. Let's see how:

Example 3.10.3. In Example 1.2.2 we needed to use row interchanges to reduce the matrix. For that reason I chose to study it again here.

$$A = \begin{bmatrix} 1 & 2 & -3 & 1 \\ 2 & 4 & 0 & 7 \\ -1 & 3 & 2 & 0 \end{bmatrix} \xrightarrow{r_2 - 2r_1 \rightarrow r_2} \begin{bmatrix} 1 & 2 & -3 & 1 \\ 0 & 0 & 6 & 5 \\ -1 & 3 & 2 & 0 \end{bmatrix} \xrightarrow{r_3 + r_1 \rightarrow r_3} \begin{bmatrix} 1 & 2 & -3 & 1 \\ 0 & 0 & 6 & 5 \\ 0 & 5 & -1 & 1 \end{bmatrix} \xrightarrow{r_2 \leftrightarrow r_3} \begin{bmatrix} 1 & 2 & -3 & 1 \\ 0 & 5 & -1 & 1 \\ 0 & 0 & 6 & 5 \end{bmatrix} = U$$

We have $U = E_3 E_2 E_1 A$ hence $A = E_1^{-1} E_2^{-1} E_3^{-1} U$ and we can calculate the product $E_1^{-1} E_2^{-1} E_3^{-1}$ as follows:

$$I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \xrightarrow{r_2 \leftrightarrow r_3} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \xrightarrow{r_3 - r_1 \rightarrow r_3} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ -1 & 1 & 0 \end{bmatrix} \xrightarrow{r_2 + 2r_1 \rightarrow r_2} \begin{bmatrix} 1 & 0 & 0 \\ 2 & 0 & 1 \\ -1 & 1 & 0 \end{bmatrix} = PL$$

I have inserted a "P" in front of the L since the matrix above is not lower triangular. However, if we go one step further and let $r_2 \leftrightarrow r_3$ then we will obtain a lower triangular matrix:

$$PL = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 0 & 1 \\ -1 & 1 & 0 \end{bmatrix} \xrightarrow{r_2 \leftrightarrow r_3} \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix} = L$$

Therefore, we find that $E_1^{-1}E_2^{-1}E_3^{-1} = PL$ where L is as above and $P = E_{2 \leftrightarrow 3}$. This means that A has a modified LU-decomposition. Some mathematicians call it a PLU-decomposition,

$$A = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}}_P \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix}}_L \underbrace{\begin{bmatrix} 1 & 2 & -3 & 1 \\ 0 & 5 & -1 & 1 \\ 0 & 0 & 6 & 5 \end{bmatrix}}_U = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 2 & 0 & 1 \\ -1 & 1 & 0 \end{bmatrix}}_{PL} \underbrace{\begin{bmatrix} 1 & 2 & -3 & 1 \\ 0 & 5 & -1 & 1 \\ 0 & 0 & 6 & 5 \end{bmatrix}}_U.$$

Since permutation matrices all satisfy the condition $P^2 = I$ the existence of a PLU-decomposition for A naturally suggests that $PA = LU$. Therefore, even when a LU decomposition is not available we can just flip a few rows to find a LU-decomposable matrix. This is a useful observation because it means that the slick algorithms developed for LU-decompositions apply to all matrices with just a little extra fine print. We'll examine how the LU-decomposition allows efficient solution of the problem $Ax = b$ at the conclusion of this section.

As I have hinted at several times, if you examine the calculation of the LU-decomposition carefully you'll see certain patterns. If no permutations are needed then whenever we make the row operation $r_j + \lambda r_k \rightarrow r_j$ it inevitably places a $-\lambda$ in the jk -position of L. Basically we just need to keep track of the λ -multipliers from each row operation. Let me do our first example in a slick notation that avoids explicit stand-alone computation of L

Example 3.10.4.

$$A = \begin{bmatrix} 1 & -1 & 1 \\ 3 & -3 & 0 \\ 2 & -2 & -3 \end{bmatrix} \xrightarrow{r_2 - 3r_1 \rightarrow r_2} \begin{bmatrix} 1 & -1 & 1 \\ (3) & 0 & -3 \\ 2 & -2 & -3 \end{bmatrix} \xrightarrow{r_3 - 2r_1 \rightarrow r_3} \begin{bmatrix} 1 & -1 & 1 \\ (3) & 0 & -3 \\ (2) & 0 & -5 \end{bmatrix} \xrightarrow{r_3 - \frac{5}{3}r_2 \rightarrow r_3} \begin{bmatrix} 1 & -1 & 1 \\ (3) & 0 & -3 \\ (2) & (\frac{5}{3}) & 0 \end{bmatrix} = U$$

The parenthetical entries are deleted to obtain U and they are inserted into the identity matrix to obtain the product $E_3^{-1}E_2^{-1}E_1^{-1}$ as follows:

$$L = \begin{bmatrix} 1 & 0 & 0 \\ 3 & 1 & 0 \\ 2 & \frac{5}{3} & 1 \end{bmatrix} \quad \text{and} \quad U = \begin{bmatrix} 1 & -1 & 1 \\ 0 & 0 & -3 \\ 0 & 0 & 0 \end{bmatrix}.$$

Which is precisely what we found before.

Example 3.10.5. Returning to our example for which $A = PLU$ let's try the slick notation and see if it still works.

$$\begin{aligned}
 A &= \begin{bmatrix} 1 & 2 & -3 & 1 \\ 2 & 4 & 0 & 7 \\ -1 & 3 & 2 & 0 \end{bmatrix} \xrightarrow{r_2 - 2r_1 \rightarrow r_2} \begin{bmatrix} 1 & 2 & -3 & 1 \\ (2) & 0 & 6 & 5 \\ -1 & 3 & 2 & 0 \end{bmatrix} \xrightarrow{r_3 + r_1 \rightarrow r_3} \\
 &\begin{bmatrix} 1 & 2 & -3 & 1 \\ (2) & 0 & 6 & 5 \\ (-1) & 5 & -1 & 1 \end{bmatrix} \xrightarrow{r_2 \leftrightarrow r_3} \begin{bmatrix} 1 & 2 & -3 & 1 \\ (-1) & 5 & -1 & 1 \\ (2) & 0 & 6 & 5 \end{bmatrix} = U
 \end{aligned}$$

We find if we remove the parenthetical entries from U and adjoining them to I then it gives back the matrix L we found previously:

$$U = \begin{bmatrix} 1 & 2 & -3 & 1 \\ 0 & 5 & -1 & 1 \\ 0 & 0 & 6 & 5 \end{bmatrix} \quad L = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix}.$$

The matrices above give us the LU -decomposition of PA where P is precisely the permutation we encountered in the calculation of U .

Remark 3.10.6.

I hope these examples are sufficient to exhibit the method. If we insist that L has units on the diagonal then I believe the factorization we have calculated is unique provided the matrix A is invertible. Uniqueness aside the application of the factorization to ladder networks is fascinating. Lay explains how the U -factor corresponds to a series circuit whereas a L -factor corresponds to a shunt circuit. The problem of finding an LU -decomposition for a given transfer matrix amounts to finding the necessary shunt and series circuits which in tandem will produce the desired transfer characteristic. We study the mathematical application of LU -decompositions in this course.

3.10.1 application of LU factorization to equation solving

Suppose we wish to solve $Ax = b$ and we are given an LU -decomposition of A . This means that we wish to solve $LUx = b$. Define $y = Ux$ and note that we then have two separate problems to solve:

$$\boxed{Ax = b, A = LU \quad \Leftrightarrow \quad \begin{array}{l} (1.) y = Ux \\ (2.) Ly = b \end{array}}.$$

It's easy to solve (2.) and then (1.).

Example 3.10.7. Solve $Ax = b$ given that

$$A = \begin{bmatrix} 1 & -1 & 1 \\ 3 & -3 & 0 \\ 2 & -2 & -3 \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 3 & 1 & 0 \\ 2 & \frac{5}{3} & 1 \end{bmatrix}}_L \underbrace{\begin{bmatrix} 1 & -1 & 1 \\ 0 & 0 & -3 \\ 0 & 0 & 0 \end{bmatrix}}_U \quad \text{and} \quad b = \begin{bmatrix} 3 \\ 1 \\ \frac{200}{3} \end{bmatrix}.$$

Solve $Ly = b$ by **forward substitution**

$$\begin{bmatrix} 1 & 0 & 0 \\ 3 & 1 & 0 \\ 2 & \frac{5}{3} & 1 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} 3 \\ 1 \\ \frac{200}{3} \end{bmatrix} \Rightarrow \begin{array}{l} y_1 = 3, \\ 9 + y_2 = 1 \Rightarrow y_2 = -8, \\ 6 - \frac{40}{3} + y_3 = \frac{200}{3} \Rightarrow y_3 = 0. \end{array}$$

Then solve $Ux = y$ by **back substitution**

$$\begin{bmatrix} 1 & -1 & 1 \\ 0 & 0 & -3 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 3 \\ -8 \\ 0 \end{bmatrix} \Rightarrow \begin{array}{l} -3x_3 = -8, \Rightarrow x_3 = 8/3, \\ x_1 + x_2 + 8/3 = 3 \Rightarrow x_1 = -1/3 - x_2. \end{array}$$

We find that $Ax = b$ has solutions of the form $(-\frac{1}{3} - t, t, \frac{8}{3})$ for $t \in \mathbb{R}$.

Note all the possibilities we encountered in previous work are still possible here. A different choice of b could make $Ax = b$ inconsistent. On the other hand, no choice of b will force a unique solution for the A considered here. In any event, it should be clear enough that forward/back substitution will provide a speedy solution to the problem $Ax = b$.

3.11 applications

Definition 3.11.1.

Let $P \in \mathbb{R}^{n \times n}$ with $P_{ij} \geq 0$ for all i, j . If the sum of the entries in any column of P is one then we say P is a stochastic matrix.

Example 3.11.2. Stochastic Matrix: A medical researcher⁴ is studying the spread of a virus in 1000 lab. mice. During any given week it's estimated that there is an 80% probability that a mouse will overcome the virus, and during the same week there is an 10% likelihood a healthy mouse will become infected. Suppose 100 mice are infected to start, (a.) how many sick next week? (b.) how many sick in 2 weeks ? (c.) after many many weeks what is the steady state solution?

$$\begin{array}{ll} I_k = \text{infected mice at beginning of week } k & \\ N_k = \text{noninfected mice at beginning of week } k & \end{array} \quad P = \begin{bmatrix} 0.2 & 0.1 \\ 0.8 & 0.9 \end{bmatrix}$$

We can study the evolution of the system through successive weeks by multiply the state-vector $X_k = [I_k, N_k]$ by the probability transition matrix P given above. Notice we are given that $X_1 = [100, 900]^T$. Calculate then,

$$X_2 = \begin{bmatrix} 0.2 & 0.1 \\ 0.8 & 0.9 \end{bmatrix} \begin{bmatrix} 100 \\ 900 \end{bmatrix} = \begin{bmatrix} 110 \\ 890 \end{bmatrix}$$

After one week there are 110 infected mice Continuing to the next week,

$$X_3 = \begin{bmatrix} 0.2 & 0.1 \\ 0.8 & 0.9 \end{bmatrix} \begin{bmatrix} 110 \\ 890 \end{bmatrix} = \begin{bmatrix} 111 \\ 889 \end{bmatrix}$$

After two weeks we have 111 mice infected. What happens as $k \rightarrow \infty$? Generally we have $X_k = PX_{k-1}$. Note that as k gets large there is little difference between k and $k-1$, in the limit they both tend to infinity. We define the steady-state solution to be $X^* = \lim_{k \rightarrow \infty} X_k$. Taking the limit of $X_k = PX_{k-1}$ as $k \rightarrow \infty$ we obtain the requirement $X^* = PX^*$. In other words, the steady state solution is found from solving $(P - I)X^* = 0$. For the example considered here we find,

$$(P - I)X^* = \begin{bmatrix} -0.8 & 0.1 \\ 0.8 & -0.1 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = 0 \quad v = 8u \quad X^* = \begin{bmatrix} u \\ 8u \end{bmatrix}$$

However, by conservation of mice, $u + v = 1000$ hence $9u = 1000$ and $u = 111.\bar{1}$ thus the steady state can be shown to be $X^* = [111.\bar{1}, 888.\bar{8}]$

Example 3.11.3. Diagonal matrices are nice: Suppose that demand for doorknobs halves every week while the demand for yo-yos it cut to 1/3 of the previous week's demand every week due to

⁴this example and most of the other applied examples in these notes are borrowed from my undergraduate linear algebra course taught from Larson's text by Dr. Terry Anderson of Appalachian State University

an amazingly bad advertising campaign⁵. At the beginning there is demand for 2 doorknobs and 5 yo-yos.

$$\begin{array}{l} D_k = \text{demand for doorknobs at beginning of week } k \\ Y_k = \text{demand for yo-yos at beginning of week } k \end{array} \quad P = \begin{bmatrix} 1/2 & 0 \\ 0 & 1/3 \end{bmatrix}$$

We can study the evolution of the system through successive weeks by multiply the state-vector $X_k = [D_k, Y_k]$ by the transition matrix P given above. Notice we are given that $X_1 = [2, 5]^T$. Calculate then,

$$X_2 = \begin{bmatrix} 1/2 & 0 \\ 0 & 1/3 \end{bmatrix} \begin{bmatrix} 2 \\ 5 \end{bmatrix} = \begin{bmatrix} 1 \\ 5/3 \end{bmatrix}$$

Notice that we can actually calculate the k -th state vector as follows:

$$X_k = P^k X_1 = \begin{bmatrix} 1/2 & 0 \\ 0 & 1/3 \end{bmatrix}^k \begin{bmatrix} 2 \\ 5 \end{bmatrix} = \begin{bmatrix} 2^{-k} & 0 \\ 0 & 3^{-k} \end{bmatrix}^k \begin{bmatrix} 2 \\ 5 \end{bmatrix} = \begin{bmatrix} 2^{-k+1} \\ 5(3^{-k}) \end{bmatrix}$$

Therefore, assuming this silly model holds for 100 weeks, we can calculate the 100-the step in the process easily,

$$X_{100} = P^{100} X_1 = \begin{bmatrix} 2^{-101} \\ 5(3^{-100}) \end{bmatrix}$$

Notice that for this example the analogue of X^* is the zero vector since as $k \rightarrow \infty$ we find X_k has components which both go to zero.

Example 3.11.4. Naive encryption: in Example 3.6.5 we found observed that the matrix A has inverse matrix A^{-1} where:

$$A = \begin{bmatrix} 1 & -1 & 0 \\ 1 & 0 & -1 \\ 6 & 2 & 3 \end{bmatrix} \quad A^{-1} = \begin{bmatrix} -2 & -3 & -1 \\ -3 & -3 & -1 \\ -2 & -4 & -1 \end{bmatrix}.$$

We use the alphabet code

$$A = 1, B = 2, C = 3, \dots, Y = 25, Z = 26$$

and a space is encoded by 0. The words are parsed into row vectors of length 3 then we multiply them by A on the right; $[\text{decoded}]A = [\text{coded}]$. Suppose we are given the string, already encoded by A

$$[9, -1, -9], [38, -19, -19], [28, -9, -19], [-80, 25, 41], [-64, 21, 31], [-7, 4, 7].$$

Find the hidden message by undoing the multiplication by A . Simply multiply by A^{-1} on the right,

$$[9, -1, -9]A^{-1}, [38, -19, -19]A^{-1}, [28, -9, -19]A^{-1},$$

⁵insert your own more interesting set of quantities that doubles/halves or triples during some regular interval of time

$$[-80, 25, 41]A^{-1}, [-64, 21, 31]A^{-1}, [-7, 4, 7]A^{-1}$$

This yields,

$$[19, 19, 0], [9, 19, 0], [3, 1, 14], [3, 5, 12], [12, 5, 4]$$

which reads *CLASS IS CANCELLED*⁶.

If you enjoy this feel free to peruse my Math 121 notes, I have additional examples of this naive encryption. I say it's naive since real encryption has much greater sophistication by this time.

Remark 3.11.5.

Matrix multiplication and the composition of linear operators is the heart of the chain rule in multivariate calculus. The derivative of a function $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ at a point $p \in \mathbb{R}^n$ gives the best linear approximation to f in the sense that

$$L_f(p+h) = f(p) + D_p f(h) \cong f(p+h)$$

if $h \in \mathbb{R}^n$ is close to the zero vector; the graph of L_f gives the tangent line or plane or hypersurface depending on the values of m, n . The so-called Frechet derivative is $D_p f$, it is a linear transformation from \mathbb{R}^n to \mathbb{R}^m . The simplest case is $f : \mathbb{R} \rightarrow \mathbb{R}$ where $D_p f(h) = f'(p)h$ and you should recognize $L_f(p+h) = f(p) + f'(p)h$ as the function whose graph is the tangent line, perhaps $L_f(x) = f(p) + f'(p)(x-p)$ is easier to see but it's the same just set $p+h=x$. Given two functions, say $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ and $g : \mathbb{R}^m \rightarrow \mathbb{R}^p$ then it can be shown that $D(g \circ f) = Dg \circ Df$. In turn, the matrix of $D(g \circ f)$ is simply obtain by multiplying the matrices of Dg and Df . The matrix of the Frechet derivative is called the Jacobian matrix. The determinant of the Jacobian matrix plays an important role in changing variables for multiple integrals. It is likely we would cover this discussion in some depth in the Advanced Calculus course, while linear algebra is not a pre-req, it sure would be nice if you had it. Linear is truly foundational for most interesting math.

⁶Larson's pg. 100-102 # 22

3.12 conclusions

The theorem that follows here collects the various ideas we have discussed concerning an $n \times n$ matrix and invertibility and solutions of $Ax = b$.

Theorem 3.12.1.

Let A be a real $n \times n$ matrix then the following are equivalent:

- (a.) A is invertible,
- (b.) $\text{rref}[A|0] = [I|0]$ where $0 \in \mathbb{R}^n$,
- (c.) $Ax = 0$ iff $x = 0$,
- (d.) A is the product of elementary matrices,
- (e.) there exists $B \in \mathbb{R}^{n \times n}$ such that $AB = I$,
- (f.) there exists $B \in \mathbb{R}^{n \times n}$ such that $BA = I$,
- (g.) $\text{rref}[A] = I$,
- (h.) $\text{rref}[A|b] = [I|x]$ for an $x \in \mathbb{R}^n$,
- (i.) $Ax = b$ is consistent for every $b \in \mathbb{R}^n$,
- (j.) $Ax = b$ has exactly one solution for every $b \in \mathbb{R}^n$,
- (k.) A^T is invertible.

These are in no particular order. If you examine the arguments in this chapter you'll find we've proved most of this theorem. What did I miss? ⁷

⁷teaching moment or me trying to get you to do my job, you be the judge.

Chapter 4

determinants

I should warn you there are some difficult calculations in this Chapter. However, the good news is these are primarily to justify the various properties of the determinant. The determinant of a square matrix is simply a number which contains lots of useful information. We will conclude this Chapter with a discussion of what the determinant says about systems of equations. There are a lot of different ways to introduce the determinant, my approach is rooted in my love of index calculations from physics. A pure mathematician would likely take another approach (mine is better). Geometrically, determinants are used to capture the idea of an oriented volume. I illustrate this with several examples before we get too deep into the more esoteric calculations.

4.1 determinants and geometry

The determinant of a square matrix can be defined by the following formulas. I'll give the general formula in the next section, but more often than not the formulas given here are more than enough. Well, this one is just silly:

$$\det a = a.$$

Then the 2×2 case is perhaps more familiar,

$$\det \begin{pmatrix} a & b \\ c & d \end{pmatrix} = ad - bc.$$

we've seen this before somewhere. Then the 3×3 formula is:

$$\det \begin{pmatrix} a & b & c \\ d & e & f \\ g & h & i \end{pmatrix} = a \cdot \det \begin{pmatrix} e & f \\ h & i \end{pmatrix} - b \cdot \det \begin{pmatrix} d & f \\ g & i \end{pmatrix} + c \cdot \det \begin{pmatrix} d & e \\ g & h \end{pmatrix}$$

and finally the 4×4 determinant is given by

$$\det \begin{pmatrix} a & b & c & d \\ e & f & g & h \\ i & j & k & l \\ m & n & o & p \end{pmatrix} = a \cdot \det \begin{pmatrix} f & g & h \\ j & k & l \\ n & o & p \end{pmatrix} - b \cdot \det \begin{pmatrix} e & g & h \\ i & k & l \\ m & o & p \end{pmatrix} \quad (4.1)$$

$$+ c \cdot \det \begin{pmatrix} e & f & h \\ i & j & l \\ m & n & p \end{pmatrix} - d \cdot \det \begin{pmatrix} e & f & g \\ i & j & k \\ m & n & o \end{pmatrix} \quad (4.2)$$

What do these formulas have to do with geometry?

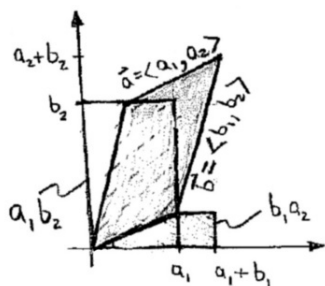
Example 4.1.1. Consider the vectors $\langle l, 0 \rangle$ and $\langle 0, w \rangle$. They make two sides of a rectangle with length l and width w . Notice

$$\det \begin{bmatrix} l & 0 \\ 0 & w \end{bmatrix} = lw.$$

In contrast,

$$\det \begin{bmatrix} 0 & w \\ l & 0 \end{bmatrix} = -lw.$$

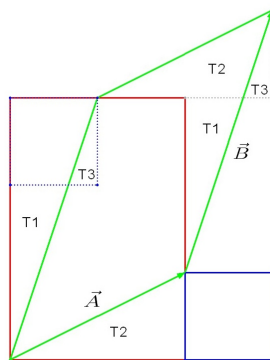
Interestingly this works for parallelograms with sides $\langle a, b \rangle$ and $\langle c, d \rangle$ the area is given by $\pm \det \begin{bmatrix} a & b \\ c & d \end{bmatrix}$.



$$\det \begin{bmatrix} \vec{a} & \vec{b} \end{bmatrix} = \det \begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \end{bmatrix} = a_1 b_2 - b_1 a_2.$$

Note, the diagram \Rightarrow Area = $a_1 b_2 - b_1 a_2$.

Maybe you can see it better in the diagram below: the point is that triangles $T1$ and $T2$ match nicely but the $T3$ is included in the red rectangle but is excluded from the green parallelogram. The area of the red rectangle A_1B_2 less the area of the blue square A_2B_1 is precisely the area of the green parallelogram.



Perhaps you recall from calculus III that we learned a parallelogram with sides \vec{A}, \vec{B} can be parametrized by $\vec{r}(u, v) = u\vec{A} + v\vec{B}$. We have $\vec{A} = (a, b, 0)$ and $\vec{B} = (c, d, 0)$ if you view the parallelogram from a three dimensional perspective. Moreover,

$$\vec{A} \times \vec{B} = \det \begin{bmatrix} e_1 & e_2 & e_3 \\ a & b & 0 \\ c & d & 0 \end{bmatrix} = (ad - bc)e_3.$$

The sign of $ad - bc$ indicates the **orientation** of the parallelogram. If the parallelogram lives in the xy -plane then it has an up-ward pointing normal if the determinant is positive whereas it has a downward pointing normal if the determinant is negative.

Example 4.1.2. If we look at a three dimensional box with vectors $\vec{A}, \vec{B}, \vec{C}$ pointing along three edges with from a common corner then it can be shown that the volume V is given by the determinant

$$V = \pm \det \begin{bmatrix} \vec{A} \\ \vec{B} \\ \vec{C} \end{bmatrix}$$

Of course it's easy to see that $V = lwh$ if the sides have length l , width w and height h . However, this formula is more general than that, it also holds if the vectors lie along a parallelepiped. Again the sign of the determinant has to do with the **orientation** of the box. If the determinant is positive then that means that the set of vectors $\{\vec{A}, \vec{B}, \vec{C}\}$ forms a righted-handed set of vectors. In terms of calculus III, \vec{C} and $\vec{A} \times \vec{B}$ both point off the same side of the plane containing \vec{A} and \vec{B} ; the ordering of the vectors is roughly consistent with the right-hand rule. If the determinant of the three vectors is negative then they will be consistent with the (inferior and evil) left-hand rule. I say "roughly" because $\vec{A} \times \vec{B}$ need not be parallel with \vec{C} .

If you study the geometry of cross and dot products it is not too hard to see that $V = |\vec{A} \cdot (\vec{B} \times \vec{C})|$.

This formula is easy to reproduce,

$$\det \begin{bmatrix} A_1 & A_2 & A_3 \\ B_1 & B_2 & B_3 \\ C_1 & C_2 & C_3 \end{bmatrix} = A_1(B_2C_3 - B_3C_2) + A_2(B_1C_3 - B_3C_1) + A_3(B_1C_2 - B_2C_1) \\ = \vec{A} \cdot (\vec{B} \times \vec{C}).$$

If you'd like to know more about the geometry of cross products then you should take calculus III and read more than Stewart. It is interesting that the determinant gives formulas for cross products and the so-called "triple product" above.

Example 4.1.3. To calculate the cross-product of \vec{A} and \vec{B} we can use the heuristic rule

$$\vec{A} \times \vec{B} = \det \begin{bmatrix} e_1 & e_2 & e_3 \\ A_1 & A_2 & A_3 \\ B_1 & B_2 & B_3 \end{bmatrix}$$

technically this is not a real "determinant" because there are vectors in the top row but numbers in the last two rows.

Example 4.1.4. The infinitesimal area element for polar coordinate is calculated from the Jacobian:

$$dS = \det \begin{bmatrix} r \sin(\theta) & -r \cos(\theta) \\ \cos(\theta) & \sin(\theta) \end{bmatrix} dr d\theta = (r \sin^2(\theta) + r \cos^2(\theta)) dr d\theta = r dr d\theta$$

Example 4.1.5. The infinitesimal volume element for cylindrical coordinate is calculated from the Jacobian:

$$dV = \det \begin{bmatrix} r \sin(\theta) & -r \cos(\theta) & 0 \\ \cos(\theta) & \sin(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} dr d\theta dz = (r \sin^2(\theta) + r \cos^2(\theta)) dr d\theta dz = r dr d\theta dz$$

Jacobians are needed to change variables in multiple integrals. The Jacobian¹ is a determinant which measures how a tiny volume is rescaled under a change of coordinates. Each row in the matrix making up the Jacobian is a tangent vector which points along the direction in which a coordinate increases when the other two coordinates are fixed.

¹see pages 206-208 of Spence Insel and Friedberg or perhaps my advanced calculus notes where I develop differentiation from a linear algebraic viewpoint.

4.2 cofactor expansion for the determinant

The precise definition of the determinant is intrinsically combinatorial. A permutation $\sigma : \mathbb{N}_n \rightarrow \mathbb{N}_n$ is a bijection. Every permutation can be written as a product of an even or odd composition of transpositions. The $\text{sgn}(\sigma) = 1$ if σ is formed from an even product of transpositions. The $\text{sgn}(\sigma) = -1$ if σ is formed from an odd product of transpositions. The sum below is over all possible permutations,

$$\det(A) = \sum_{\sigma} \text{sgn}(\sigma) A_{1\sigma(1)} A_{2\sigma(2)} \cdots A_{n\sigma(n)}$$

this provides an explicit definition of the determinant. For example, in the $n = 2$ case we have $\sigma_o(x) = x$ or $\sigma_1(1) = 2, \sigma_1(2) = 1$. The sum over all permutations has just two terms in the $n = 2$ case,

$$\det(A) = \text{sgn}(\sigma_o) A_{1\sigma_o(1)} A_{2\sigma_o(2)} + \text{sgn}(\sigma_1) A_{1\sigma_1(1)} A_{2\sigma_1(2)} = A_{11} A_{22} - A_{12} A_{21}$$

In the notation $A_{11} = a, A_{12} = b, A_{21} = c, A_{22} = d$ the formula above says $\det(A) = ad - bc$.

Pure mathematicians tend to prefer the definition above to the one I am preparing below. I would argue mine has the advantage of not summing over functions. My sums are simply over integers. The calculations I make in the proofs in this Chapter may appear difficult to you, but if you gain a little more experience with index calculations I think you would find them accessible. I will not go over them all in lecture. I would recommend you at least read over them.

Definition 4.2.1.

Let $\epsilon_{i_1 i_2 \dots i_n}$ be defined to be the completely antisymmetric symbol in n -indices. We define $\epsilon_{12 \dots n} = 1$ then all other values are generated by demanding the interchange of any two indices is antisymmetric. This is also known as the **Levi-Civita** symbol.

We have nice formulas for the determinant with the help of the Levi-Civita symbol, the following is yet another way of stating the definition for $\det(A)$,

$$\det(A) = \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, i_2, \dots, i_n} A_{1i_1} A_{2i_2} \cdots A_{ni_n}$$

Example 4.2.2. *I prefer this definition. I can actually calculate it faster, for example the $n = 3$ case is pretty quick:*

$$\begin{aligned} \det(A) = & \epsilon_{123} A_{11} A_{22} A_{33} + \epsilon_{231} A_{12} A_{23} A_{31} + \epsilon_{312} A_{13} A_{21} A_{32} \\ & + \epsilon_{321} A_{13} A_{22} A_{31} + \epsilon_{213} A_{12} A_{21} A_{33} + \epsilon_{132} A_{11} A_{23} A_{32} \end{aligned}$$

In principle there are 27 terms above but only these 6 are nontrivial because if any index is repeated the ϵ_{ijk} is zero. The only nontrivial terms are $\epsilon_{123} = \epsilon_{231} = \epsilon_{312} = 1$ and $\epsilon_{321} = \epsilon_{213} = \epsilon_{132} = -1$. Thus,

$$\begin{aligned} \det(A) = & A_{11} A_{22} A_{33} + A_{12} A_{23} A_{31} + A_{13} A_{21} A_{32} \\ & - A_{13} A_{22} A_{31} - A_{12} A_{21} A_{33} - A_{11} A_{23} A_{32} \end{aligned}$$

This formula is much closer to the trick-formula for calculating the determinant without using minors. (I'll put it on the board in class, it is above my skill-level for these notes)

The formalism above will be used in all my proofs. I take the Levi-Civita definition as the primary definition for the determinant. All other facts flow from that source. The cofactor expansions of the determinant could also be used as a definition.

Definition 4.2.3.

Let $A = [A_{ij}] \in \mathbb{R}^{n \times n}$. The minor of A_{ij} is denoted M_{ij} which is defined to be the determinant of the $\mathbb{R}^{(n-1) \times (n-1)}$ matrix formed by deleting the i -th column and the j -th row of A . The (i, j) -th co-factor of A is $C_{ij} = (-1)^{i+j} M_{ij}$.

Theorem 4.2.4.

The determinant of $A \in \mathbb{R}^{n \times n}$ can be calculated from a sum of cofactors either along any row or column;

1. $\det(A) = A_{i1}C_{i1} + A_{i2}C_{i2} + \cdots + A_{in}C_{in}$ (i -th row expansion)
2. $\det(A) = A_{1j}C_{1j} + A_{2j}C_{2j} + \cdots + A_{nj}C_{nj}$ (j -th column expansion)

Proof: I'll attempt to sketch a proof of (2.) directly from the general definition. Let's try to identify A_{1i_1} with A_{1j} then A_{2i_2} with A_{2j} and so forth, keep in mind that j is a fixed but arbitrary index, it is not summed over.

$$\begin{aligned}
 \det(A) &= \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, i_2, \dots, i_n} A_{1i_1} A_{2i_2} \cdots A_{ni_n} \\
 &= \sum_{i_2, \dots, i_n} \epsilon_{j, i_2, \dots, i_n} A_{1j} A_{2i_2} \cdots A_{ni_n} + \sum_{i_1 \neq j, i_2, \dots, i_n} \epsilon_{i_1, i_2, \dots, i_n} A_{1i_1} A_{2i_2} \cdots A_{ni_n} \\
 &= \sum_{i_2, \dots, i_n} \epsilon_{j, i_2, \dots, i_n} A_{1j} A_{2i_2} \cdots A_{ni_n} + \sum_{i_1 \neq j, i_3, \dots, i_n} \epsilon_{i_1, j, \dots, i_n} A_{1i_1} A_{2j} \cdots A_{ni_n} \\
 &\quad + \cdots + \sum_{i_1 \neq j, i_2 \neq j, \dots, i_{n-1} \neq j} \epsilon_{i_1, i_2, \dots, i_{n-1}, j} A_{1i_1} \cdots A_{n-1, i_{n-1}} A_{nj} \\
 &\quad + \sum_{i_1 \neq j, \dots, i_n \neq j} \epsilon_{i_1, \dots, i_n} A_{1i_1} A_{1i_2} \cdots A_{ni_n}
 \end{aligned}$$

Consider the summand. If all the indices $i_1, i_2, \dots, i_n \neq j$ then there must be at least one repeated index in each list of such indices. Consequently the last sum vanishes since $\epsilon_{i_1, \dots, i_n}$ is zero if any two indices are repeated. We can pull out A_{1j} from the first sum, then A_{2j} from the second sum,

and so forth until we eventually pull out A_{nj} out of the last sum.

$$\begin{aligned} \det(A) &= A_{1j} \left(\sum_{i_2, \dots, i_n} \epsilon_{j, i_2, \dots, i_n} A_{2i_2} \cdots A_{ni_n} \right) + A_{2j} \left(\sum_{i_1 \neq j, \dots, i_n} \epsilon_{i_1, j, \dots, i_n} A_{1i_1} \cdots A_{ni_n} \right) + \cdots \\ &\quad + A_{nj} \left(\sum_{i_1 \neq j, i_2 \neq j, \dots, i_{n-1} \neq j} \epsilon_{i_1, i_2, \dots, j} A_{1i_1} A_{2i_2} \cdots A_{n-1, i_{n-1}} \right) \end{aligned}$$

The terms appear different, but in fact there is a hidden symmetry. If any index in the summations above takes the value j then the Levi-Civita symbol will have two j 's and hence those terms are zero. Consequently we can just as well take all the sums over all values **except** j . In other words, each sum is a completely antisymmetric sum of products of $n - 1$ terms taken from all columns except j . For example, the first term has an antisymmetrized sum of a product of $n - 1$ terms not including column j or row 1. Reordering the indices in the Levi-Civita symbol generates a sign of $(-1)^{1+j}$ thus the first term is simply $A_{1j}C_{1j}$. Likewise the next summand is $A_{2j}C_{2j}$ and so forth until we reach the last term which is $A_{nj}C_{nj}$. In other words,

$$\boxed{\det(A) = A_{1j}C_{1j} + A_{2j}C_{2j} + \cdots + A_{nj}C_{nj}}$$

The proof of (1.) is probably similar. We will soon learn that $\det(A^T) = \det(A)$ thus (2.) \implies (1.). since the j -th row of A^T is the j -th columns of A .

All that remains is to show why $\det(A) = \det(A^T)$. Recall $(A^T)_{ij} = A_{ji}$ for all i, j , thus

$$\begin{aligned} \det(A^T) &= \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, i_2, \dots, i_n} (A^T)_{1i_1} (A^T)_{2i_2} \cdots (A^T)_{ni_n} \\ &= \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, i_2, \dots, i_n} A_{i_1 1} A_{i_2 2} \cdots A_{i_n n} \\ &= \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, i_2, \dots, i_n} A_{1i_1} A_{2i_2} \cdots A_{ni_n} = \det(A) \end{aligned}$$

to make the last step one need only see that both sums contain all the same terms just written in a different order. Let me illustrate explicitly how this works in the $n = 3$ case,

$$\begin{aligned} \det(A^T) &= \epsilon_{123} A_{11} A_{22} A_{33} + \epsilon_{231} A_{21} A_{32} A_{13} + \epsilon_{312} A_{31} A_{12} A_{23} \\ &\quad + \epsilon_{321} A_{31} A_{22} A_{13} + \epsilon_{213} A_{21} A_{12} A_{33} + \epsilon_{132} A_{11} A_{32} A_{23} \end{aligned}$$

The I write the entries so the column indices go 1, 2, 3

$$\begin{aligned} \det(A^T) &= \epsilon_{123} A_{11} A_{22} A_{33} + \epsilon_{231} A_{13} A_{21} A_{32} + \epsilon_{312} A_{12} A_{23} A_{31} \\ &\quad + \epsilon_{321} A_{13} A_{22} A_{31} + \epsilon_{213} A_{12} A_{21} A_{33} + \epsilon_{132} A_{11} A_{23} A_{32} \end{aligned}$$

But, the indices of the Levi-Civita symbol are not in the right order yet. Fortunately, we have identities such as $\epsilon_{231} = \epsilon_{312}$ which allow us to reorder the indices without introducing any new signs,

$$\begin{aligned} \det(A^T) &= \epsilon_{123}A_{11}A_{22}A_{33} + \epsilon_{312}A_{13}A_{21}A_{32} + \epsilon_{231}A_{12}A_{23}A_{31} \\ &\quad + \epsilon_{321}A_{13}A_{22}A_{31} + \epsilon_{213}A_{12}A_{21}A_{33} + \epsilon_{132}A_{11}A_{23}A_{32} \end{aligned}$$

But, these are precisely the terms in $\det(A)$ just written in a different order (see Example 4.2.2). Thus $\det(A^T) = \det(A)$. I leave the details of how to reorder the order n sum to the reader. \square

Remark 4.2.5.

Lay's text circumnavigates many of the difficulties I face in this chapter by using the co-factor definition as the definition of the determinant. One place you can also find a serious treatment of determinants is in *Linear Algebra* by Insel, Spence and Friedberg where you'll find the proof of the co-factor expansion is somewhat involved. However, the heart of the proof involves multilinearity. Multilinearity is practically manifest with our Levi-Civita definition. Anywho, a better definition for the determinant is as follows: **the determinant is the alternating, n -multilinear, real valued map such that $\det(I) = 1$.** It can be shown this uniquely defines the determinant. All these other things like permutations and the Levi-Civita symbol are just notation.

Remark 4.2.6.

The best way to prove things about determinants is likely the wedge product formalism. In that notation the Levi-Civita symbol is implicit within the so-called wedge product of vectors. For a $n \times n$ matrix the $\det(A)$ is defined implicitly by the formula $\text{col}_1(A) \wedge \text{col}_2(A) \wedge \cdots \wedge \text{col}_n(A) = \det(A)e_1 \wedge e_2 \wedge \cdots \wedge e_n$. One nice place to read more about these things from a purely linear-algebraic perspective is the text *Abstract Linear Algebra* by Morton L. Curtis.

Example 4.2.7. *I suppose it's about time for an example. Let*

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$$

I usually calculate by expanding across the top row out of habit,

$$\begin{aligned} \det(A) &= 1\det \begin{bmatrix} 5 & 6 \\ 8 & 9 \end{bmatrix} - 2\det \begin{bmatrix} 4 & 6 \\ 7 & 9 \end{bmatrix} + 3\det \begin{bmatrix} 4 & 5 \\ 7 & 8 \end{bmatrix} \\ &= 1(45 - 48) - 2(36 - 42) + 3(32 - 35) \\ &= -3 + 12 - 9 \\ &= 0. \end{aligned}$$

Now, we could also calculate by expanding along the middle row,

$$\begin{aligned} \det(A) &= -4\det \begin{bmatrix} 2 & 3 \\ 8 & 9 \end{bmatrix} + 5\det \begin{bmatrix} 1 & 3 \\ 7 & 9 \end{bmatrix} - 6\det \begin{bmatrix} 1 & 2 \\ 7 & 8 \end{bmatrix} \\ &= -4(18 - 24) + 5(9 - 21) - 6(8 - 14) \\ &= 24 - 60 + 36 \\ &= 0. \end{aligned}$$

Many other choices are possible, for example expand along the right column,

$$\begin{aligned} \det(A) &= 3\det \begin{bmatrix} 4 & 5 \\ 7 & 8 \end{bmatrix} - 6\det \begin{bmatrix} 1 & 2 \\ 7 & 8 \end{bmatrix} + 9\det \begin{bmatrix} 1 & 2 \\ 4 & 5 \end{bmatrix} \\ &= 3(32 - 35) - 6(8 - 14) + 9(5 - 8) \\ &= -9 + 36 - 27 \\ &= 0. \end{aligned}$$

which is best? Certain matrices might have a row or column of zeros, then it's easiest to expand along that row or column.

Example 4.2.8. Let's look at an example where we can exploit the co-factor expansion to greatly reduce the difficulty of the calculation. Let

$$A = \begin{bmatrix} 1 & 2 & 3 & 0 & 4 \\ 0 & 0 & 5 & 0 & 0 \\ 6 & 7 & 8 & 0 & 0 \\ 0 & 9 & 3 & 4 & 0 \\ -1 & -2 & -3 & 0 & 1 \end{bmatrix}$$

Begin by expanding down the 4-th column,

$$\det(A) = (-1)^{4+4}M_{44} = 4\det \begin{bmatrix} 1 & 2 & 3 & 4 \\ 0 & 0 & 5 & 0 \\ 6 & 7 & 8 & 0 \\ -1 & -2 & -3 & 1 \end{bmatrix}$$

Next expand along the 2-row of the remaining determinant,

$$\det(A) = (4)(5)(-1)^{2+3}M_{23} = -20\det \begin{bmatrix} 1 & 2 & 4 \\ 6 & 7 & 0 \\ -1 & -2 & 1 \end{bmatrix}$$

Finish with the trick for 3×3 determinants, it helps me to write out

$$\left[\begin{array}{ccc|cc} 1 & 2 & 4 & 1 & 2 \\ 6 & 7 & 0 & 6 & 7 \\ -1 & -2 & 1 & -1 & -2 \end{array} \right]$$

then calculate the products of the three down diagonals and the three upward diagonals. Subtract the up-diagonals from the down-diagonals.

$$\det(A) = -20(7 + 0 - 48 - (-28) - (0) - (12)) = -20(-25) = 500.$$

4.3 properties of determinants

We're finally getting towards the good part.

Proposition 4.3.1.

Let $A \in \mathbb{R}^{n \times n}$,

1. $\det(A^T) = \det(A)$,
2. If there exists j such that $\text{row}_j(A) = 0$ then $\det(A) = 0$,
3. If there exists j such that $\text{col}_j(A) = 0$ then $\det(A) = 0$,
4. $\det[A_1|A_2|\cdots|aA_k+bB_k|\cdots|A_n] = a\det[A_1|\cdots|A_k|\cdots|A_n] + b\det[A_1|\cdots|B_k|\cdots|A_n]$,
5. $\det(kA) = k^n\det(A)$
6. if $B = \{A : r_k \leftrightarrow r_j\}$ then $\det(B) = -\det(A)$,
7. if $B = \{A : r_k + ar_j \rightarrow r_k\}$ then $\det(B) = \det(A)$,
8. if $\text{row}_i(A) = k\text{row}_j(A)$ for $i \neq j$ then $\det(A) = 0$

where I mean to denote $r_k \leftrightarrow r_j$ as the row interchange and $r_k + ar_j \rightarrow r_k$ as a column addition and I assume $k < j$.

Proof: we already proved (1.) in the proof of the cofactor expansion Theorem 4.2.4. The proof of (2.) and (3.) follows immediately from the cofactor expansion if we expand along the zero row or column. The proof of (4.) is not hard given our Levi-Civita definition, let

$$C = [A_1|A_2|\cdots|aA_k+bB_k|\cdots|A_n]$$

Calculate from the definition,

$$\begin{aligned}
 \det(C) &= \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, i_2, \dots, i_n} C_{1i_1} \cdots C_{ki_k} \cdots C_{ni_n} \\
 &= \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, i_2, \dots, i_n} A_{1i_1} \cdots (aA_{ki_k} + bB_{ki_k}) \cdots A_{ni_n} \\
 &= a \left(\sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, i_2, \dots, i_n} A_{1i_1} \cdots A_{ki_k} \cdots A_{ni_n} \right) \\
 &\quad + b \left(\sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, i_2, \dots, i_n} A_{1i_1} \cdots B_{ki_k} \cdots A_{ni_n} \right) \\
 &= a \det[A_1 | A_2 | \cdots | A_k | \cdots | A_n] + b \det[A_1 | A_2 | \cdots | B_k | \cdots | A_n].
 \end{aligned}$$

by the way, the property above is called multilinearity. The proof of (5.) is similar,

$$\begin{aligned}
 \det(kA) &= \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, i_2, \dots, i_n} kA_{1i_1} kA_{2i_2} \cdots kA_{ni_n} \\
 &= k^n \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, i_2, \dots, i_n} A_{1i_1} A_{2i_2} \cdots A_{ni_n} \\
 &= k^n \det(A)
 \end{aligned}$$

Let B be as in (6.), this means that $\text{col}_k(B) = \text{col}_j(A)$ and vice-versa,

$$\begin{aligned}
 \det(B) &= \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, \dots, i_k, \dots, i_j, \dots, i_n} A_{1i_1} \cdots A_{ji_k} \cdots A_{ki_j} \cdots A_{ni_n} \\
 &= \sum_{i_1, i_2, \dots, i_n} -\epsilon_{i_1, \dots, i_j, \dots, i_k, \dots, i_n} A_{1i_1} \cdots A_{ji_k} \cdots A_{ki_j} \cdots A_{ni_n} \\
 &= -\det(A)
 \end{aligned}$$

where the minus sign came from interchanging the indices i_j and i_k .

To prove (7.) let us define B as in the Proposition: let $\text{row}_k(B) = \text{row}_k(A) + a\text{row}_j(A)$ and $\text{row}_i(B) = \text{row}_i(A)$ for $i \neq k$. This means that $B_{kl} = A_{kl} + aA_{jl}$ and $B_{il} = A_{il}$ for each l .

Consequently,

$$\begin{aligned}
 \det(B) &= \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, \dots, i_k, \dots, i_n} A_{1i_1} \cdots (A_{ki_k} + aA_{ji_k}) \cdots A_{ni_n} \\
 &= \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, \dots, i_n} A_{1i_1} \cdots A_{ki_k} \cdots A_{ni_n} \\
 &\quad + a \left(\sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, \dots, i_j, \dots, i_k, \dots, i_n} A_{1i_1} \cdots A_{ji_j} \cdots A_{ji_k} \cdots A_{ni_n} \right) \\
 &= \sum_{i_1, i_2, \dots, i_n} \epsilon_{i_1, \dots, i_n} A_{1i_1} \cdots A_{ki_k} \cdots A_{ni_n} \\
 &= \det(A).
 \end{aligned}$$

The term in parenthesis vanishes because it has the sum of an antisymmetric tensor in i_j, i_k against a symmetric tensor in i_j, i_k . Here is the pattern, suppose $S_{ij} = S_{ji}$ and $T_{ij} = -T_{ji}$ for all i, j then consider

$$\begin{aligned}
 \sum_i \sum_j S_{ij} T_{ij} &= \sum_j \sum_i S_{ji} T_{ji} && \text{switched indices} \\
 &= \sum_j \sum_i -S_{ij} T_{ij} && \text{used sym. and antisym.} \\
 &= - \sum_i \sum_j S_{ij} T_{ij} && \text{interchanged sums.}
 \end{aligned}$$

thus we have $\sum S_{ij} T_{ij} = - \sum S_{ij} T_{ij}$ which indicates the sum is zero. We can use the same argument on the pair of indices i_j, i_k in the expression since $A_{ji_j} A_{ji_k}$ is symmetric in i_j, i_k whereas the Levi-Civita symbol is antisymmetric in i_j, i_k .

We get (8.) as an easy consequence of (2.) and (7.), just subtract one row from the other so that we get a row of zeros. \square

Proposition 4.3.2.

The determinant of a diagonal matrix is the product of the diagonal entries.

Proof: Use multilinearity on each row,

$$\det \begin{bmatrix} d_1 & 0 & \cdots & 0 \\ 0 & d_2 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & d_n \end{bmatrix} = d_1 \det \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & d_2 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & d_n \end{bmatrix} = \cdots = d_1 d_2 \cdots d_n \det \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix}$$

Thus $\det(D) = d_1 d_2 \cdots d_n$ as claimed. \square

Proposition 4.3.3.

Let L be a lower triangular square matrix and U be an upper triangular square matrix.

1. $\det(L) = L_{11}L_{22} \cdots L_{nn}$
2. $\det(U) = U_{11}U_{22} \cdots U_{nn}$

Proof: I'll illustrate the proof of (2.) for the 3×3 case. We use the co-factor expansion across the first column of the matrix to begin,

$$\det \begin{bmatrix} U_{11} & U_{12} & U_{13} \\ 0 & U_{22} & U_{23} \\ 0 & 0 & U_{33} \end{bmatrix} = U_{11} \det \begin{bmatrix} U_{22} & U_{23} \\ 0 & U_{33} \end{bmatrix} = U_{11}U_{22}U_{33}$$

The proof of the $n \times n$ case is essentially the same. For (1.) use the co-factor expansion across the top row of L , to get $\det(L) = L_{11}C_{11}$. Note the submatrix for calculating C_{11} is again has a row of zeros across the top. We calculate $C_{11} = L_{22}C_{22}$. This continues all the way down the diagonal. We find $\det(L) = L_{11}L_{22} \cdots L_{nn}$. \square

Proposition 4.3.4.

Let $A \in \mathbb{R}^{n \times n}$ and $k \neq 0 \in \mathbb{R}$,

1. $\det(E_{r_i \leftrightarrow r_j}) = -1$,
2. $\det(E_{kr_i \rightarrow r_i}) = k$,
3. $\det(E_{r_i + br_j \rightarrow r_i}) = 1$,
4. for any square matrix B and elementary matrix E , $\det(EB) = \det(E)\det(B)$
5. if E_1, E_2, \dots, E_k are elementary then $\det(E_1E_2 \cdots E_k) = \det(E_1)\det(E_2) \cdots \det(E_k)$

Proof: Proposition 4.6.2 shows us that $\det(I) = 1$ since $I^{-1} = I$ (there are many easier ways to show that). Note then that $E_{r_i \leftrightarrow r_j}$ is a row-swap of the identity matrix thus by Proposition 4.3.1 we find $\det(E_{r_i \leftrightarrow r_j}) = -1$. To prove (2.) we use multilinearity from Proposition 4.3.1. For (3.) we use multilinearity again to show that:

$$\det(E_{r_i + br_j \rightarrow r_i}) = \det(I) + b\det(E_{ij})$$

Again $\det(I) = 1$ and since the unit matrix E_{ij} has a row of zeros we know by Proposition 4.3.1 $\det(E_{ij}) = 0$.

To prove (5.) we use Proposition 4.3.1 multiple times in the arguments below. Let $B \in \mathbb{R}^{n \times n}$ and suppose E is an elementary matrix. If E is multiplication of a row by k then $\det(E) = k$ from (2.). Also EB is the matrix B with some row multiplied by k . Use multilinearity to see that

$\det(EB) = k\det(B)$. Thus $\det(EB) = \det(E)\det(B)$. If E is a row interchange then EB is B with a row swap thus $\det(EB) = -\det(B)$ and $\det(E) = -1$ thus we again find $\det(EB) = \det(E)\det(B)$. Finally, if E is a row addition then EB is B with a row addition and $\det(EB) = \det(B)$ and $\det(E) = 1$ hence $\det(EB) = \det(E)\det(B)$. Notice that (6.) follows by repeated application of (5.). \square

Proposition 4.3.5.

A square matrix A is invertible iff $\det(A) \neq 0$.

Proof: recall there exist elementary matrices E_1, E_2, \dots, E_k such that $rref(A) = E_1 E_2 \cdots E_k A$. Thus $\det(rref(A)) = \det(E_1)\det(E_2) \cdots \det(E_k)\det(A)$. Either $\det(rref(A)) = 0$ and $\det(A) = 0$ or they are both nonzero.

Suppose A is invertible. Then $Ax = 0$ has a unique solution and thus $rref(A) = I$ hence $\det(rref(A)) = 1 \neq 0$ implying $\det(A) \neq 0$.

Conversely, suppose $\det(A) \neq 0$, then $\det(rref(A)) \neq 0$. But this means that $rref(A)$ does not have a row of zeros. It follows $rref(A) = I$. Therefore $A^{-1} = E_1 E_2 \cdots E_k$. \square

Proposition 4.3.6.

If $A, B \in \mathbb{R}^{n \times n}$ then $\det(AB) = \det(A)\det(B)$.

Proof: If either A or B is not invertible then the reduced row echelon form of the noninvertible matrix will have a row of zeros hence $\det(A)\det(B) = 0$. Without loss of generality, assume A is not invertible. Note $rref(A) = E_1 E_2 \cdots E_k A$ hence $E_3^{-1} E_2^{-1} E_1^{-1} rref(A) B = AB$. Notice that $rref(A) B$ will have at least one row of zeros since $rref(A)$ has a row of zeros. Thus $\det(E_3^{-1} E_2^{-1} E_1^{-1} rref(A) B) = \det(E_3^{-1} E_2^{-1} E_1^{-1}) \det(rref(A) B) = 0$.

Suppose that both A and B are invertible. Then there exist elementary matrices such that $A = E_1 \cdots E_p$ and $B = E_{p+1} \cdots E_{p+q}$ thus

$$\begin{aligned} \det(AB) &= \det(E_1 \cdots E_p E_{p+1} \cdots E_{p+q}) \\ &= \det(E_1 \cdots E_p) \det(E_{p+1} \cdots E_{p+q}) \\ &= \det(A) \det(B). \end{aligned}$$

We made repeated use of (6.) in Proposition 4.3.4. \square

Proposition 4.3.7.

If $A \in \mathbb{R}^{n \times n}$ is invertible then $\det(A^{-1}) = \frac{1}{\det(A)}$.

Proof: If A is invertible then there exists $A^{-1} \in \mathbb{R}^{n \times n}$ such that $AA^{-1} = I$. Apply Proposition 4.3.6 to see that

$$\det(AA^{-1}) = \det(A)\det(A^{-1}) = \det(I) \Rightarrow \det(A)\det(A^{-1}) = 1.$$

Thus, $\det(A^{-1}) = 1/\det(A)$ \square

Many of the properties we used to prove $\det(AB) = \det(A)\det(B)$ are easy to derive if you were simply given the assumption $\det(AB) = \det(A)\det(B)$. When you look at what went into the proof of Proposition 4.3.6 it's not surprising that $\det(AB) = \det(A)\det(B)$ is a powerful formula to know.

Proposition 4.3.8.

If A is block-diagonal with square blocks A_1, A_2, \dots, A_k then

$$\det(A) = \det(A_1)\det(A_2) \cdots \det(A_k).$$

Proof: for a 2×2 matrix this is clearly true since a block diagonal matrix is simply a diagonal matrix. In the 3×3 nondiagonal case we have a 2×2 block A_1 paired with a single diagonal entry A_2 . Simply apply the cofactor expansion on the row of the diagonal entry to find that $\det(A) = A_2\det(A_1) = \det(A_2)\det(A_1)$. For a 4×4 we have more cases but similar arguments apply. I leave the general proof to the reader. \square

Example 4.3.9. If $M = \left[\begin{array}{c|c} A & 0 \\ \hline 0 & B \end{array} \right]$ is a block matrix where A, B are square blocks then $\det(M) = \det(A)\det(B)$.

4.4 examples of determinants

In the preceding section I worked pretty hard to prove a number of useful properties for determinants. I show how to use them in this section.

Example 4.4.1. Notice that row 2 is twice row 1,

$$\det \begin{bmatrix} 1 & 2 & 3 \\ 2 & 4 & 6 \\ 7 & 8 & 9 \end{bmatrix} = 0.$$

Example 4.4.2. To calculate this one we make a single column swap to get a diagonal matrix.

The determinant of a diagonal matrix is the product of the diagonals, thus:

$$\det \begin{bmatrix} 0 & 6 & 0 & 0 & 0 & 0 \\ 8 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} = -\det \begin{bmatrix} 6 & 0 & 0 & 0 & 0 & 0 \\ 0 & 8 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} = 48.$$

Example 4.4.3. I choose the the column/row for the co-factor expansion to make life easy each time:

$$\begin{aligned} \det \begin{bmatrix} 0 & 1 & 0 & 2 \\ 13 & 71 & 5 & \pi \\ 0 & 3 & 0 & 4 \\ -2 & e & 0 & G \end{bmatrix} &= -5\det \begin{bmatrix} 0 & 1 & 2 \\ 0 & 3 & 4 \\ -2 & e & G \end{bmatrix} \\ &= -5(-2)\det \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \\ &= 10(4 - 6) \\ &= -20. \end{aligned}$$

Example 4.4.4. Find the values of λ such that the matrix $A - \lambda I$ is singular given that

$$A = \begin{bmatrix} 1 & 0 & 2 & 3 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 3 \end{bmatrix}$$

The matrix $A - \lambda I$ is singular iff $\det(A - \lambda I) = 0$,

$$\begin{aligned} \det(A - \lambda I) &= \det \begin{bmatrix} 1 - \lambda & 0 & 2 & 3 \\ 1 & -\lambda & 0 & 0 \\ 0 & 0 & 2 - \lambda & 0 \\ 0 & 0 & 0 & 3 - \lambda \end{bmatrix} \\ &= (3 - \lambda)\det \begin{bmatrix} 1 - \lambda & 0 & 2 \\ 1 & \lambda & 0 \\ 0 & 0 & 2 - \lambda \end{bmatrix} \\ &= (3 - \lambda)(2 - \lambda)\det \begin{bmatrix} 1 - \lambda & 0 \\ 1 & \lambda \end{bmatrix} \\ &= (3 - \lambda)(2 - \lambda)(1 - \lambda)(-\lambda) \\ &= \lambda(\lambda - 1)(\lambda - 2)(\lambda - 3) \end{aligned}$$

Thus we need $\lambda = 0, 1, 2$ or 3 in order that $A - \lambda I$ be a noninvertible matrix. These values are called the **eigenvalues** of A . We will have much more to say about that later.

Example 4.4.5. Suppose we are given the LU -factorization of a particular matrix (borrowed from the text by Spence, Insel and Friedberg see Example 2 on pg. 154-155.)

$$A = \begin{bmatrix} 1 & -1 & 2 \\ 3 & -1 & 7 \\ 2 & -4 & 5 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 3 & 1 & 0 \\ 2 & -1 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 & 2 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix} = LU$$

The LU -factorization is pretty easy to find, we may discuss that at the end of the course. It is an important topic if you delve into serious numerical work where you need to write your own code and so forth. Anyhow, notice that L, U are triangular so we can calculate the determinant very easily,

$$\det(A) = \det(L)\det(U) = 1 \cdot 1 \cdot 1 \cdot 1 \cdot 2 \cdot 2 = 4.$$

From a numerical perspective, the LU -factorization is a superior method for calculating $\det(A)$ as compared to the co-factor expansion. It has much better "convergence" properties. Incidentally, your text has much more to say about algorithmics so please keep that in mind if my comments here leave you wanting more.

Example 4.4.6. Recall that the columns in A are linearly independent iff $Ax = 0$ has only the $x = 0$ solution. We also found that the existence of A^{-1} was equivalent to that claim in the case A was square since $Ax = 0$ implies $A^{-1}Ax = A^{-1}0 = 0$ hence $x = 0$. Clearly then the columns of a square matrix A are linearly independent iff A^{-1} exists. Suppose A^{-1} exists then $AA^{-1} = I$ thus $\det(AA^{-1}) = \det(A)\det(A^{-1}) = \det(I) = 1$ hence $\det(A) \neq 0$. Conversely, the adjoint formula for the inverse is well-defined if $\det(A) \neq 0$. To summarize: for $A \in \mathbb{R}^{n \times n}$

columns of A are linearly independent $\Leftrightarrow \det(A) \neq 0$.
--

Observe that this criteria is only useful if we wish to examine the linear independence of precisely n -vectors in \mathbb{R}^n . For example, $(1, 1, 1), (1, 0, 1), (2, 1, 2) \in \mathbb{R}^3$ have

$$\det \left[\begin{array}{c|c|c} 1 & 1 & 2 \\ 1 & 0 & 1 \\ 1 & 1 & 2 \end{array} \right] = 0.$$

Therefore, $\{(1, 1, 1), (1, 0, 1), (2, 1, 2)\}$ form a linearly dependent set of vectors.

4.5 Kramer's Rule

The numerical methods crowd seem to think this is a loathsome brute. It is an incredibly clumsy way to calculate the solution of a system of equations $Ax = b$. Moreover, Kramer's rule fails in the case $\det(A) = 0$ so it's not nearly as general as our other methods. However, it does help calculate the variation of parameters formulas in differential equations so it is still of theoretical interest at a minimum. Students sometimes like it because it gives you a *formula* to find the solution. Students sometimes incorrectly jump to the conclusion that a formula is easier than say a *method*. It is certainly wrong here, the method of Gaussian elimination beats Kramer's rule by just about every objective criteria in so far as concrete numerical examples are concerned.

Proposition 4.5.1.

If $Ax = b$ is a linear system of equations with $x = [x_1 \ x_2 \ \cdots \ x_n]^T$ and $A \in \mathbb{R}^{n \times n}$ such that $\det(A) \neq 0$ then we find solutions

$$x_1 = \frac{\det(A_1)}{\det(A)}, \quad x_2 = \frac{\det(A_2)}{\det(A)}, \quad \dots, \quad x_n = \frac{\det(A_n)}{\det(A)}$$

where we define A_k to be the $n \times n$ matrix obtained by replacing the k -th column of A by the inhomogeneous term b .

Proof: Since $\det(A) \neq 0$ we know that $Ax = b$ has a unique solution. Suppose $x_j = \frac{\det(A_j)}{\det(A)}$ where $A_j = [col_1(A) | \cdots | col_{j-1}(A) | b | col_{j+1}(A) | \cdots | col_n(A)]$. We seek to show $x = [x_j]$ is a solution to $Ax = b$. Notice that the n -vector equations

$$Ae_1 = col_1(A), \dots, Ae_{j-1} = col_{j-1}(A), Ae_{j+1} = col_{j+1}(A), \dots, Ae_n = col_n(A), Ax = b$$

can be summarized as a single matrix equation:

$$A[e_1 | \dots | e_{j-1} | x | e_{j+1} | \dots | e_n] = \underbrace{[col_1(A) | \dots | col_{j-1}(A) | b | col_{j+1}(A) | \dots | col_n(A)]}_{\text{this is precisely } A_j} = A_j$$

Notice that if we expand on the j -th column it's obvious that

$$\det[e_1 | \dots | e_{j-1} | x | e_{j+1} | \dots | e_n] = x_j$$

Returning to our matrix equation, take the determinant of both sides and use that the product of the determinants is the determinant of the product to obtain:

$$\det(A)x_j = \det(A_j)$$

Since $\det(A) \neq 0$ it follows that $x_j = \frac{\det(A_j)}{\det(A)}$ for all j . \square

This is the proof that is given in Lay's text. The construction of the matrix equation is not really an obvious step in my estimation. Whoever came up with this proof originally realized that he

would need to use the determinant product identity to overcome the subtlety in the proof. Once you realize that then it's natural to look for that matrix equation. This is a clever proof²

Example 4.5.2. Solve $Ax = b$ given that

$$A = \begin{bmatrix} 1 & 3 \\ 2 & 8 \end{bmatrix} \quad b = \begin{bmatrix} 1 \\ 5 \end{bmatrix}$$

where $x = [x_1 \ x_2]^T$. Apply Kramer's rule, note $\det(A) = 2$,

$$x_1 = \frac{1}{2} \det \begin{bmatrix} 1 & 3 \\ 5 & 8 \end{bmatrix} = \frac{1}{2}(8 - 15) = \frac{-7}{2}.$$

and,

$$x_2 = \frac{1}{2} \det \begin{bmatrix} 1 & 1 \\ 2 & 5 \end{bmatrix} = \frac{1}{2}(5 - 2) = \frac{3}{2}.$$

The original system of equations would be $x_1 + 3x_2 = 1$ and $2x_1 + 8x_2 = 5$. As a quick check we can substitute in our answers $x_1 = -7/2$ and $x_2 = 3/2$ and see if they work.

Example 4.5.3. An nonhomogeneous system of linear, constant coefficient ordinary differential equations can be written as a matrix differential equation:

$$\frac{dx}{dt} = Ax + f$$

It turns out we'll be able to solve the homogeneous system $dx/dt = Ax$ via something called the matrix exponential. Long story short, we'll find n -solutions which we can concatenate into one big matrix solution X . To solve the given nonhomogeneous problem one makes the ansatz that $x = Xv$ is a solution for some yet unknown vector of functions. Then calculus leads to the problem of solving

$$X \frac{dv}{dt} = f$$

where X is matrix of functions, dv/dt and f are vectors of functions. X is invertible so we expect to find a unique solution dv/dt . Kramer's rule says,

$$\left(\frac{dv}{dt} \right)_i = \frac{1}{\det(X)} \det[\vec{x}_1 | \cdots | g | \cdots | \vec{x}_n] = \frac{W_i[f]}{\det(X)} \quad \text{defining } W_i \text{ in the obvious way}$$

For each i we integrate the equation above,

$$v_i(t) = \int \frac{W_i[f] dt}{\det(X)}.$$

The general solution is thus,

$$x = Xv = X \left[\int \frac{W_i[f] dt}{\det(X)} \right].$$

²as seen from my humble vantage point naturally

The first component of this formula justifies n -th order variation of parameters. For example in the $n = 2$ case you may have learned that $y_p = y_1 v_1 + y_2 v_2$ solves $ay'' + by' + cy = g$ if

$$v_1 = \int \frac{-gy_2 dt}{y_1 y_2' - y_2 y_1'} \quad v_2 = \int \frac{gy_1 dt}{y_1 y_2' - y_2 y_1'}$$

These come from the general result above. Notice that these formulas need $y_1 y_2' - y_2 y_1' \neq 0$. This is precisely the **Wronskian** $W[y_1, y_2] = y_1 y_2' - y_2 y_1'$ of the fundamental solutions y_1, y_2 . It turns out that the Wronskian is nonzero for fundamental solutions thus the formulas above are entirely general. Linear independence of functions is considerably trickier than linear independence in \mathbb{R}^n , I'll say more in the chapter on vector spaces.

Example 4.5.4. here's a problem from Advanced calculus last year. I use Kramer's rule to calculate derivatives of variables which are implicitly defined by several equations. The idea is rather simple; take the total differential of each constraint equation then solve for the differentials of the independent variables in terms of the dependent variables. The total differentials give linear relations between all the differentials of the variables where the coefficients are functions.

Problem 5 [300pts] Suppose that

$$x^2 + y + z + e^w = 2 \quad \text{and} \quad x + y^2 + z + w^3 = 0.$$

Calculate $\left(\frac{\partial w}{\partial x}\right)_z$. State which variables are dependent and which are independent at the start of your calculation.

Use w, y dependent on independent x, z

$$2x dx + dy + dz + e^w dw = 0$$

$$dx + 2y dy + dz + 3w^2 dw = 0$$

$$dy + e^w dw = -2x dx - dz$$

$$2y dy + 3w^2 dw = -dx - dz$$

$$\begin{bmatrix} 1 & e^w \\ 2y & 3w^2 \end{bmatrix} \begin{bmatrix} dy \\ dw \end{bmatrix} = \begin{bmatrix} -2x dx - dz \\ -dx - dz \end{bmatrix}$$

$$dw = \frac{\det \begin{bmatrix} 2y & -2x dx - dz \\ -dx - dz & 3w^2 \end{bmatrix}}{3w^2 - 2y e^w}$$

$$= -dx - dz + 2y(2x dx + dz)$$

$$= (4xy - 1) dx + (2y - 1) dz \quad \therefore \left(\frac{\partial w}{\partial x}\right)_z = 4xy - 1$$

4.6 adjoint matrix

Definition 4.6.1.

Let $A \in \mathbb{R}^{n \times n}$ the the matrix of cofactors is called the **adjoint** of A . It is denoted $\text{adj}(A)$ and is defined by and $\text{adj}(A)_{ij} = C_{ij}^T$ where C_{ij} is the (i, j) -th cofactor.

I'll keep it simple here, lets look at the 2×2 case:

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

has cofactors $C_{11} = (-1)^{1+1}\det(d) = d$, $C_{12} = (-1)^{1+2}\det(c) = -c$, $C_{21} = (-1)^{2+1}\det(b) = -b$ and $C_{22} = (-1)^{2+2}\det(a) = a$. Collecting these results,

$$\text{adj}(A) = \begin{bmatrix} d & -c \\ -b & a \end{bmatrix}$$

This is interesting. Recall we found a formula for the inverse of A (if it exists). The formula was

$$A^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

Notice that $\det(A) = ad - bc$ thus in the 2×2 case the relation between the inverse and the adjoint is rather simple:

$$A^{-1} = \frac{1}{\det(A)} \text{adj}(A)^T$$

It turns out this is true for larger matrices as well:

Proposition 4.6.2.

If A is invertible then $A^{-1} = \frac{1}{\det(A)} \text{adj}(A)^T$.

Proof I: Calculate the product of A and $\text{adj}(A)^T$,

$$A \text{adj}(A)^T = \begin{bmatrix} A_{11} & A_{21} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{bmatrix} \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{n1} \\ C_{12} & C_{22} & \cdots & C_{n2} \\ \vdots & \vdots & \cdots & \vdots \\ C_{1n} & C_{2n} & \cdots & C_{nn} \end{bmatrix}$$

The (i, j) -th component of the product above is

$$(A \text{adj}(A)^T)_{ij} = \text{row}_i(A) \text{col}_j(\text{adj}(A)^T) = \text{row}_i(A) \text{row}_j(\text{adj}(A)) = A_{i1}C_{j1} + A_{i2}C_{j2} + \cdots + A_{in}C_{jn}$$

Suppose that $i = j$ then the sum above is precisely the i -th row co-factor expansion for $\det(A)$:

$$(A \text{adj}(A)^T)_{ij} = A_{i1}C_{i1} + A_{i2}C_{i2} + \cdots + A_{in}C_{in} = \det(A)$$

If $i \neq j$ then the sum vanishes. I leave the details to the reader³ \square

Proof II: To find the inverse of A we need only apply Kramer's rule to solve the equations implicit within $AA^{-1} = I$. Let $A^{-1} = [v_1|v_2|\cdots|v_n]$ we need to solve

$$Av_1 = e_1, \quad Av_2 = e_2, \quad \dots \quad Av_n = e_n$$

Kramer's rule gives us $(v_1)_j = \frac{C_{1j}}{\det(A)}$ where $C_{1j} = (-1)^{1+j}M_{1j}$ is the cofactor formed from deleting the first row and j -th column. More generally we may apply Kramer's rule to deduce the j -component of the i -th column in the inverse $(v_i)_j = \frac{C_{ij}}{\det(A)}$. Therefore, $col_i(A^{-1})_j = (A^{-1})_{ji} = \frac{C_{ij}}{\det(A)}$. By definition $adj(A) = [C_{ij}]$ hence $adj(A)_{ij}^T = C_{ji}$ and it follows that $A^{-1} = \frac{1}{\det(A)}adj(A)^T$. \square

Example 4.6.3. *Let's calculate the general formula for the inverse of a 3×3 matrix. Assume it exists for the time being. (the criteria for the inverse existing is staring us in the face everywhere here). Let*

$$A = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$$

Calculate the cofactors,

$$C_{11} = \det \begin{bmatrix} e & f \\ h & i \end{bmatrix} = ei - fh,$$

$$C_{12} = -\det \begin{bmatrix} d & f \\ g & i \end{bmatrix} = fg - di,$$

$$C_{13} = \det \begin{bmatrix} d & e \\ g & h \end{bmatrix} = dh - eg,$$

$$C_{21} = -\det \begin{bmatrix} b & c \\ h & i \end{bmatrix} = ch - bi,$$

$$C_{22} = \det \begin{bmatrix} a & c \\ g & i \end{bmatrix} = ai - cg,$$

$$C_{23} = -\det \begin{bmatrix} a & b \\ g & h \end{bmatrix} = bg - ah,$$

$$C_{31} = \det \begin{bmatrix} b & c \\ e & f \end{bmatrix} = bf - ce,$$

$$C_{32} = -\det \begin{bmatrix} a & c \\ d & f \end{bmatrix} = cd - af,$$

$$C_{33} = \det \begin{bmatrix} a & b \\ d & e \end{bmatrix} = ae - bd.$$

³I don't have an easy proof that these terms cancel for $i \neq j$. It's simply to verify for the $n = 2$ or $n = 3$ cases but the reason appears to be a combinatorial cancellation. If you can provide a concrete and readable proof for the general case it would definitely earn you some points.

Hence the adjoint is

$$\text{adj}(A) = \left[\begin{array}{c|c|c} ei - fh & fg - di & dh - eg \\ \hline ch - bi & ai - cg & bg - ah \\ \hline bf - ce & cd - af & ae - bd \end{array} \right]$$

Thus, using the $A^{-1} = \det(A)\text{adj}(A)^T$

$$\left[\begin{array}{ccc} a & b & c \\ d & e & f \\ g & h & i \end{array} \right]^{-1} = \frac{1}{aei + bfg + cdh - gec - hfa - idb} \left[\begin{array}{c|c|c} ei - fh & ch - bi & bf - ce \\ \hline fg - di & ai - cg & cd - af \\ \hline dh - eg & bg - ah & ae - bd \end{array} \right]$$

You should notice that are previous method for finding A^{-1} is far superior to this method. It required much less calculation. Let's check my formula in the case $A = 3I$, this means $a = e = i = 3$ and the others are zero.

$$I^{-1} = \frac{1}{27} \left[\begin{array}{c|c|c} 9 & 0 & 0 \\ \hline 0 & 9 & 0 \\ \hline 0 & 0 & 9 \end{array} \right] = \frac{1}{3}I$$

This checks, $(3I)(\frac{1}{3}I) = \frac{3}{3}II = I$. I do not recommend that you memorize this formula to calculate inverses for 3×3 matrices.

4.7 applications

The determinant is a convenient mnemonic to create expressions which are antisymmetric. The key property is that if we switch a row or column it creates a minus sign. This means that if any two rows are repeated then the determinant is zero. Notice this is why the cross product of two vectors is naturally phrased in terms of a determinant. The antisymmetry of the determinant insures the formula for the cross-product will have the desired antisymmetry. In this section we examine a few more applications for the determinant.

Example 4.7.1. *The Pauli's exclusion principle in quantum mechanics states that the wave function of a system of fermions is antisymmetric. Given N -electron wavefunctions $\chi_1, \chi_2, \dots, \chi_N$ the following is known as the **Slater Determinant***

$$\Psi(\vec{r}_1, \vec{r}_2, \dots, \vec{r}_N) = \det \begin{bmatrix} \chi_1(\vec{r}_1) & \chi_2(\vec{r}_1) & \cdots & \chi_N(\vec{r}_1) \\ \chi_1(\vec{r}_2) & \chi_2(\vec{r}_2) & \cdots & \chi_N(\vec{r}_2) \\ \vdots & \vdots & \cdots & \vdots \\ \chi_1(\vec{r}_N) & \chi_2(\vec{r}_N) & \cdots & \chi_N(\vec{r}_N) \end{bmatrix}$$

Notice that $\Psi(\vec{r}_1, \vec{r}_1, \dots, \vec{r}_N) = 0$ and generally if any two of the position vectors $\vec{r}_i = \vec{r}_j$ then the total wavefunction $\Psi = 0$. In quantum mechanics the wavefunction's modulus squared gives the probability density of finding the system in a particular circumstance. In this example, the fact that any repeated entry gives zero means that no two electrons can share the same position. This is characteristic of particles with half-integer **spin**, such particles are called **fermions**. In contrast, **bosons** are particles with integer spin and they can occupy the same space. For example, light is made of photons which have spin 1 and in a laser one finds many waves of light traveling in the same space.

Example 4.7.2. *This is an example of a Vandermonde determinant. Note the following curious formula:*

$$\det \begin{bmatrix} 1 & x_1 & y_1 \\ 1 & x_2 & y_2 \\ 1 & x & y \end{bmatrix} = 0$$

Let's reduce this by row-operations⁴

$$\begin{bmatrix} 1 & x_1 & y_1 \\ 1 & x_2 & y_2 \\ 1 & x & y \end{bmatrix} \xrightarrow[r_3 - r_1 \rightarrow r_3]{r_2 - r_1 \rightarrow r_2} \begin{bmatrix} 1 & x_1 & y_1 \\ 0 & x_2 - x_1 & y_2 - y_1 \\ 0 & x - x_1 & y - y_1 \end{bmatrix}$$

Notice that the row operations above could be implemented by multiply on the left by $E_{r_2-r_1 \rightarrow r_2}$ and $E_{r_3-r_1 \rightarrow r_3}$. These are invertible matrices and thus $\det(E_{r_2-r_1 \rightarrow r_2}) = k_1$ and $\det(E_{r_3-r_1 \rightarrow r_3}) = k_2$

⁴of course we could calculate it straight from the co-factor expansion, I merely wish to illustrate how we can use row operations to simplify a determinant

for some pair of nonzero constants k_1, k_2 . If X is the given matrix and Y is the reduced matrix above then $Y = E_{r_3-r_1 \rightarrow r_3} E_{r_2-r_1 \rightarrow r_2} X$ thus,

$$\begin{aligned} 0 = \det \begin{bmatrix} 1 & x_1 & y_1 \\ 1 & x_2 & y_2 \\ 1 & x & y \end{bmatrix} &= k_1 k_2 \det \begin{bmatrix} 1 & x_1 & y_1 \\ 0 & x_2 - x_1 & y_2 - y_1 \\ 0 & x - x_1 & y - y_1 \end{bmatrix} \\ &= k_1 k_2 [(x_2 - x_1)(y - y_1) - (y_2 - y_1)(x - x_1)] \end{aligned}$$

Divide by $k_1 k_2$ and rearrange to find:

$$(x_2 - x_1)(y - y_1) = (y_2 - y_1)(x - x_1) \quad \Rightarrow \quad \boxed{y = y_1 + \left(\frac{y_2 - y_1}{x_2 - x_1} \right) (x - x_1)}$$

The boxed equation is the famous two-point formula for a line.

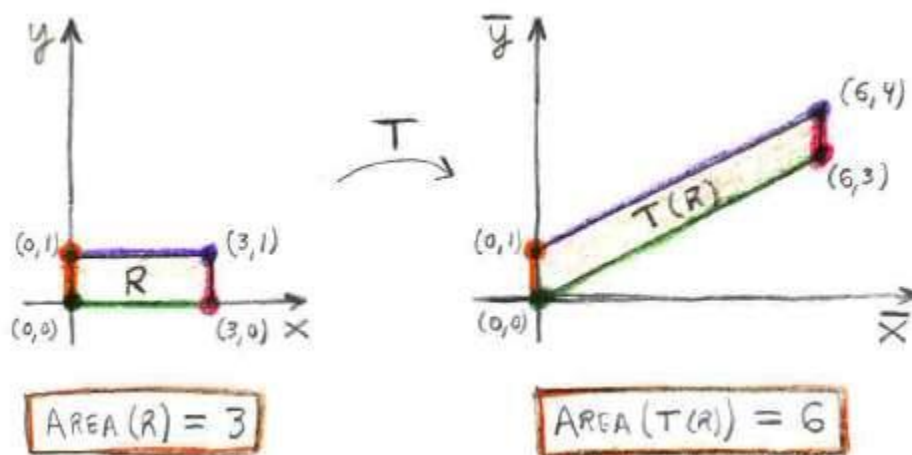
Example 4.7.3. Let us consider a linear transformation $T([x, y]^T) = [2x, x + y]^T$. Furthermore, let's see how a rectangle R with corners $(0, 0)$, $(3, 0)$, $(3, 1)$, $(0, 1)$. Since this linear transformation is invertible (I invite you to prove that) it follows that the image of a line is again a line. Therefore, if we find the image of the corners under the mapping T then we can just connect the dots in the image to see what $T(R)$ resembles. Our goal here is to see what a linear transformation does to a rectangle.

$$T([0, 0]^T) = [0, 0]^T$$

$$T([3, 0]^T) = [6, 3]^T$$

$$T([3, 1]^T) = [6, 4]^T$$

$$T([0, 1]^T) = [0, 1]^T$$



As you can see from the picture we have a parallelogram with base 6 and height 1 thus $\text{Area}(T(R)) = 6$. In contrast, $\text{Area}(R) = 3$. You can calculate that $\det(T) = 2$. Curious, $\text{Area}(T(R)) = \det(T)\text{Area}(R)$. I wonder if this holds in general? ⁵

⁵ok, actually I don't wonder, I just make it your homework problem.

4.8 conclusions

We continue Theorem 3.12.1 from the previous chapter.

Theorem 4.8.1.

Let A be a real $n \times n$ matrix then the following are equivalent:

- (a.) A is invertible,
- (b.) $rref[A|0] = [I|0]$ where $0 \in \mathbb{R}^n$,
- (c.) $Ax = 0$ iff $x = 0$,
- (d.) A is the product of elementary matrices,
- (e.) there exists $B \in \mathbb{R}^{n \times n}$ such that $AB = I$,
- (f.) there exists $B \in \mathbb{R}^{n \times n}$ such that $BA = I$,
- (g.) $rref[A] = I$,
- (h.) $rref[A|b] = [I|x]$ for an $x \in \mathbb{R}^n$,
- (i.) $Ax = b$ is consistent for every $b \in \mathbb{R}^n$,
- (j.) $Ax = b$ has exactly one solution for every $b \in \mathbb{R}^n$,
- (k.) A^T is invertible,
- (l.) $\det(A) \neq 0$,
- (m.) Kramer's rule yields solution of $Ax = b$ for every $b \in \mathbb{R}^n$.

It's a small addition, however the determinant is a nice tool for small systems since it's pretty easy to calculate. Also, Kramer's rule is nice for small systems since it just gives us the solution. This is all a very special case, in general we could have an inconsistent system or infinitely many solutions.

Theorem 4.8.2.

Let A be a real $n \times n$ matrix then the following are equivalent:

- (a.) A is not invertible,
- (b.) $Ax = 0$ has at least one nontrivial solution.,
- (c.) there exists $b \in \mathbb{R}^n$ such that $Ax = b$ is inconsistent,
- (d.) $\det(A) = 0$,

It turns out this theorem is also useful. We shall see it is fundamental to the theory of eigenvectors.

Chapter 5

linear algebra

Up to this point the topics we have discussed loosely fit into the category of matrix theory. The concept of a matrix is milienia old. If I trust my source, and I think I do, the Chinese even had an analogue of Gaussian elimination about 2000 years ago. The modern notation likely stems from the work of Cauchy in the 19-th century. Cauchy's prolific work colors much of the notation we still use. The theory of determinants occupied much of the professional mathematicians' for a large part of the 19-th century. Determinants produce all sorts of useful formulae, but in the modern view they play a secondary role. The concept of coordinate geometry as introduced by Descartes and Fermat around 1644 is what ultimately led to the concept of a vector space.¹ Grassmann, Hamilton, and many many others worked out volumous work detailing possible transformations on what we now call $\mathbb{R}^2, \mathbb{R}^3, \mathbb{R}^4, .$ Argand(complex numbers) and Hamilton(quaternions) had more than what we would call a vector space. They had a linear structure plus some rule for multiplication of vectors. A vector space with a multiplication is called an *algebra* in the modern terminology.

Honestly, I think once the concept of the Cartesian plane was discovered the concept of a vector space almost certainly must follow. That said, it took a while for the definition I state in the next section to appear. Giuseppe Peano gave the modern definition for a vector space in 1888². In addition he put forth some of the ideas concerning linear transformations which we discuss in the next chapter. Peano is also responsible for the modern notations for intersection and unions of sets³. He made great contributions to proof by induction and the construction of the natural numbers from basic set theory.

Finally, I should mention the work of Hilbert, Lebesque, Fourier, Banach and others were greatly influential in the formation of infinite dimensional vector spaces. Our focus is on the finite dimensional case.⁴

¹ Bourbaki 1969, ch. "Algebre lineaire et algebre multilineaire", pp. 7891.

²Peano, Giuseppe (1888), *Calcolo Geometrico secondo l'Ausdehnungslehre di H. Grassmann preceduto dalle Operazioni della Logica Deduttiva*, Turin

³see Pg 87 of A Transition to Advanced Mathematics: A Survey Course By William Johnston

⁴this history is flawed, one-sided and far too short. You should read a few more books if you're interested.

Finally, let me summarize what a vector space is before we define it. In short, a vector space over \mathbb{F} is simply a set which allows you to add its elements and multiply by the numbers in \mathbb{F} . The theorems and overall layout of this chapter mirror Chapter 5 of Anton and Rorres' *Elementary Linear Algebra* (9-th ed.).

5.1 definition and examples

Axioms are not derived from a more basic logic. They are the starting point. Their validity is ultimately judged by their use. However, this definition is naturally motivated by the structure of vector addition and scalar multiplication in \mathbb{R}^n (see Proposition 2.2.9)

Definition 5.1.1.

A vector space V over \mathbb{R} is a set V together with a function $+: V \times V \rightarrow V$ called **vector addition** and another function $\cdot: \mathbb{R} \times V \rightarrow V$ called **scalar multiplication**. We require that the operations of vector addition and scalar multiplication satisfy the following 10 axioms: for all $x, y, z \in V$ and $a, b \in \mathbb{R}$,

1. (A1) $x + y = y + x$ for all $x, y \in V$,
2. (A2) $(x + y) + z = x + (y + z)$ for all $x, y, z \in V$,
3. (A3) there exists $0 \in V$ such that $x + 0 = x$ for all $x \in V$,
4. (A4) for each $x \in V$ there exists $-x \in V$ such that $x + (-x) = 0$,
5. (A5) $1 \cdot x = x$ for all $x \in V$,
6. (A6) $(ab) \cdot x = a \cdot (b \cdot x)$ for all $x \in V$ and $a, b \in \mathbb{R}$,
7. (A7) $a \cdot (x + y) = a \cdot x + a \cdot y$ for all $x, y \in V$ and $a \in \mathbb{R}$,
8. (A8) $(a + b) \cdot x = a \cdot x + b \cdot x$ for all $x \in V$ and $a, b \in \mathbb{R}$,
9. (A9) If $x, y \in V$ then $x + y$ is a single element in V , (we say V is closed with respect to addition)
10. (A10) If $x \in V$ and $c \in \mathbb{R}$ then $c \cdot x$ is a single element in V . (we say V is closed with respect to scalar multiplication)

We call 0 in axiom 3 the **zero vector** and the vector $-x$ is called the **additive inverse** of x . We will sometimes omit the \cdot and instead denote scalar multiplication by juxtaposition; $a \cdot x = ax$.

Axioms (9.) and (10.) are admittedly redundant given that those automatically follow from the statements that $+: V \times V \rightarrow V$ and $\cdot: \mathbb{R} \times V \rightarrow V$ are functions. I've listed them so that you are

less likely to forget they must be checked.

The terminology "vector" does not necessarily indicate an explicit geometric interpretation in this general context. Sometimes I'll insert the word "abstract" to emphasize this distinction. We'll see that matrices, polynomials and functions in general can be thought of as abstract vectors.

Example 5.1.2. \mathbb{R} is a vector space if we identify addition of real numbers as the vector addition and multiplication of real numbers as the scalar multiplication.

The preceding example is very special because we can actually multiply the vectors. Usually we cannot multiply vectors.

Example 5.1.3. Proposition 2.2.9 shows \mathbb{R}^n forms a vector space with respect to the standard vector addition and scalar multiplication.

Example 5.1.4. The set of all $m \times n$ matrices is denoted $\mathbb{R}^{m \times n}$. It forms a vector space with respect to matrix addition and scalar multiplication as we defined previously. Notice that we cannot mix matrices of differing sizes since we have no natural way of adding them.

Example 5.1.5. The set of all linear transformations from \mathbb{R}^n to \mathbb{R}^m is denoted $L(\mathbb{R}^n, \mathbb{R}^m)$. Define addition and scalar multiplication of the transformations in the natural manner: if $S, T \in L(\mathbb{R}^n, \mathbb{R}^m)$ then for $c \in \mathbb{R}$ and each $v \in \mathbb{R}^n$

$$(S + T)(v) = S(v) + T(v), \quad (c \cdot T)(v) = cT(v).$$

we can show $S + T \in L(\mathbb{R}^n, \mathbb{R}^m)$ and $c \cdot T \in L(\mathbb{R}^n, \mathbb{R}^m)$ and the other axioms follow easily.

Example 5.1.6. Let $\mathcal{F}(\mathbb{R})$ denote the set of all functions with domain \mathbb{R} . Let $f, g \in \mathcal{F}(\mathbb{R})$ and suppose $c \in \mathbb{R}$, define addition of functions by

$$(f + g)(x) \equiv f(x) + g(x)$$

for all $x \in \mathbb{R}$. Likewise for $f \in \mathcal{F}(\mathbb{R})$ and $c \in \mathbb{R}$ define scalar multiplication of a function by a constant in the obvious way:

$$(cf)(x) = cf(x)$$

for all $x \in \mathbb{R}$. In short, we define addition and scalar multiplication by the natural "point-wise" rules. Notice we must take functions which share the same domain since otherwise we face difficulty in choosing the domain for the new function $f + g$, we can also consider functions sharing a common domain $I \subset \mathbb{R}$ and denote that by $\mathcal{F}(I)$. These are called function spaces.

Example 5.1.7. Let $P_2 = \{ax^2 + bx + c \mid a, b, c \in \mathbb{R}\}$, the set of all polynomials up to quadratic order. Define addition and scalar multiplication by the usual operations on polynomials. Notice that if $ax^2 + bx + c, dx^2 + ex + f \in P_2$ then

$$(ax^2 + bx + c) + (dx^2 + ex + f) = (a + d)x^2 + (b + e)x + (c + f) \in P_2$$

thus $+: P_2 \times P_2 \rightarrow P_2$ (it is a binary operation on P_2). Similarly,

$$d(ax^2 + bx + c) = dax^2 + dbx + dc \in P_2$$

thus scalar multiplication maps $\mathbb{R} \times P_2 \rightarrow P_2$ as it ought. Verification of the other 8 axioms is straightfoward. We denote the set of polynomials of order n or less via $P_n = \{a_n x^n + \cdots + a_1 x + a_0 \mid a_i \in \mathbb{R}\}$. Naturally, P_n also forms a vector space. Finally, if we take the set of all polynomials P it forms a vector space. Notice,

$$P_2 \subset P_3 \subset P_4 \subset \cdots \subset P$$

The theorem that follows is full of seemingly obvious facts. Each of these facts can be **derived** from the vector space axioms.

Theorem 5.1.8.

Let V be a vector space with zero vector 0 and let $c \in \mathbb{R}$,

1. $0 \cdot x = 0$ for all $x \in V$,
2. $c \cdot 0 = 0$ for all $c \in \mathbb{R}$,
3. $(-1) \cdot x = -x$ for all $x \in V$,
4. if $cx = 0$ then $c = 0$ or $x = 0$.

Lemma 5.1.9. Law of Cancellation:

Let a, x, y be vectors in a vector space V . If $x + a = y + a$ then $x = y$.

Proof of Lemma: Suppose $x + a = y + a$. By A4 there exists $-a$ such that $a + (-a) = 0$. Thus $x + a = y + a$ implies $(x + a) + (-a) = (y + a) + (-a)$. By A2 we find $x + (a + (-a)) = y + (a + (-a))$ which gives $x + 0 = y + 0$. Continuing we use A3 to obtain $x + 0 = 0$ and $y + 0 = y$ and consequently $x = y$. \square

Proof of Theorem: Begin with (1.). Let $x \in V$, notice that by A6,

$$2 \cdot (0 \cdot x) = (2 \cdot 0) \cdot x = 0 \cdot x.$$

By A8 and A6,

$$2 \cdot (0 \cdot x) = (1 + 1) \cdot (0 \cdot x) = 1 \cdot (0 \cdot x) + 1 \cdot (0 \cdot x) = (1 \cdot 0) \cdot x + (1 \cdot 0) \cdot x = 0 \cdot x + 0 \cdot x.$$

Thus, $0 \cdot x = 0 \cdot x + 0 \cdot x$ and by A3 we find $0 + 0 \cdot x = 0 \cdot x + 0 \cdot x$. Using the Lemma we cancel off the $0 \cdot x$ on both sides leaving $0 = 0 \cdot x$. Since x was arbitrary it follows that $0 \cdot x = 0$ for all $x \in V$.

I'm leaving (2.), (3.) and (4.) as exercises for the reader. What makes these challenging is you have to fight the urge to use things we have yet to prove true. Essentially, all we have to work with is the cancellation Lemma and the vector space axioms. \square

5.2 subspaces

Definition 5.2.1.

Let V be a vector space. If $W \subseteq V$ such that W is a vector space with respect to the operations of V restricted to W then we say that W is a **subspace** of V and we write $W \leq V$.

Example 5.2.2. Let V be a vector space. Notice that $V \subseteq V$ and obviously V is a vector space with respect to its operations. Therefore $V \leq V$. Likewise, the set containing the zero vector $\{0\} \leq V$. Notice that $0 + 0 = 0$ and $c \cdot 0 = 0$ so Axioms 9 and 10 are satisfied. I leave the other axioms to the reader. The subspace $\{0\}$ is called the **trivial subspace**.

Example 5.2.3. Let $L = \{(x, y) \in \mathbb{R}^2 \mid ax + by = 0\}$. Define addition and scalar multiplication by the natural rules in \mathbb{R}^2 . Note if $(x, y), (z, w) \in L$ then $(x, y) + (z, w) = (x + z, y + w)$ and $a(x + z) + b(y + w) = ax + by + az + bw = 0 + 0 = 0$ hence $(x, y) + (z, w) \in L$. Likewise, if $c \in \mathbb{R}$ and $(x, y) \in L$ then $ax + by = 0$ implies $acx + bcy = 0$ thus $(cx, cy) = c(x, y) \in L$. We find that L is closed under vector addition and scalar multiplication. The other 8 axioms are naturally inherited from \mathbb{R}^2 . This makes L a **subspace** of \mathbb{R}^2 .

Example 5.2.4. If $V = \mathbb{R}^3$ then

1. $\{(0, 0, 0)\}$ is a subspace,
2. any line through the origin is a subspace,
3. any plane through the origin is a subspace.

Example 5.2.5. Let $W = \{(x, y, z) \mid x + y + z = 1\}$. Is this a subspace of \mathbb{R}^3 ? The answer is no. There are many reasons,

1. $(0, 0, 0) \notin W$ thus W has no zero vector, axiom 3 fails. Notice we cannot change the idea of "zero" for the subspace, if $(0, 0, 0)$ is zero for \mathbb{R}^3 then it is the only zero for potential subspaces. Why? Because subspaces inherit their structure from the vector space which contains them.
2. let $(u, v, w), (a, b, c) \in W$ then $u + v + w = 1$ and $a + b + c = 1$, however $(u + a, v + b, w + c) \notin W$ since $(u + a) + (v + b) + (w + c) = (u + v + w) + (a + b + c) = 1 + 1 = 2$.
3. let $(u, v, w) \in W$ then notice that $2(u, v, w) = (2u, 2v, 2w)$. Observe that $2u + 2v + 2w = 2(u + v + w) = 2$ hence $(2u, 2v, 2w) \notin W$. Thus axiom 10 fails, the subset W is not closed under scalar multiplication.

Of course, one reason is all it takes.

My focus on the last two axioms is not without reason. Let me explain this obsession.

Theorem 5.2.6.

Let V be a vector space and suppose $W \subset V$ with $W \neq \emptyset$ then $W \leq V$ if and only if the following two conditions hold true

1. if $x, y \in W$ then $x + y \in W$ (W is closed under addition),
2. if $x \in W$ and $c \in \mathbb{R}$ then $c \cdot x \in W$ (W is closed under scalar multiplication).

Proof: (\Rightarrow) If $W \leq V$ then W is a vector space with respect to the operations of addition and scalar multiplication thus (1.) and (2.) hold true.

(\Leftarrow) Suppose W is a nonempty set which is closed under vector addition and scalar multiplication of V . We seek to prove W is a vector space with respect to the operations inherited from V . Let $x, y, z \in W$ then $x, y, z \in V$. Use A1 and A2 for V (which were given to begin with) to find

$$x + y = y + x \quad \text{and} \quad (x + y) + z = x + (y + z).$$

Thus A1 and A2 hold for W . By (3.) of Theorem 5.1.8 we know that $(-1) \cdot x = -x$ and $-x \in W$ since we know W is closed under scalar multiplication. Consequently, $x + (-x) = 0 \in W$ since W is closed under addition. It follows A3 is true for W . Then by the arguments just given A4 is true for W . Let $a, b \in \mathbb{R}$ and notice that by A5, A6, A7, A8 for V we find

$$1 \cdot x = x, \quad (ab) \cdot x = a \cdot (b \cdot x), \quad a \cdot (x + y) = a \cdot x + a \cdot y, \quad (a + b) \cdot x = a \cdot x + b \cdot x.$$

Thus A5, A6, A7, A8 likewise hold for W . Finally, we assumed closure of addition and scalar multiplication on W so A9 and A10 are likewise satisfied and we conclude that W is a vector space. Thus $W \leq V$. (if you're wondering where we needed W nonempty it was to argue that there exists at least one vector x and consequently the zero vector is in W .) \square

Remark 5.2.7.

The application of Theorem 5.2.6 is a four-step process

1. check that $W \subset V$
2. check that $0 \in W$
3. take arbitrary $x, y \in W$ and show $x + y \in W$
4. take arbitrary $x \in W$ and $c \in \mathbb{R}$ and show $cx \in W$

Step (2.) is just for convenience, you could just as well find another vector in W . We need to find at least one to show that W is nonempty. Also, usually we omit comment about (1.) since it is obvious that one set is a subset of another.

Example 5.2.8. The function space $\mathcal{F}(\mathbb{R})$ has many subspaces.

1. continuous functions: $C(\mathbb{R})$
2. differentiable functions: $C^1(\mathbb{R})$
3. smooth functions: $C^\infty(\mathbb{R})$
4. polynomial functions
5. analytic functions
6. solution set of a linear homogeneous ODE with no singular points

The proof that each of these follows from Theorem 5.2.6. For example, $f(x) = x$ is continuous therefore $C(\mathbb{R}) \neq \emptyset$. Moreover, the sum of continuous functions is continuous and a scalar multiple of a continuous function is continuous. Thus $C(\mathbb{R}) \leq \mathcal{F}(\mathbb{R})$. The arguments for (2.), (3.), (4.), (5.) and (6.) are identical. The solution set example is one of the most important examples for engineering and physics, linear ordinary differential equations.

Example 5.2.9. The null space of a matrix $A \in \mathbb{R}^{m \times n}$ is a subspace of $\mathbb{R}^{m \times 1}$ defined as follows:

$$\text{Null}(A) \equiv \{x \in \mathbb{R}^{m \times 1} \mid Ax = 0\}$$

Let's prove $\text{Null}(A) \leq \mathbb{R}^{m \times 1}$. Observe that $A0 = 0$ hence $0 \in \text{Null}(A)$ so the nullspace is nonempty. Suppose $x, y \in \text{Null}(A)$ and $c \in \mathbb{R}$,

$$A(x + cy) = Ax + cAy = 0 + c(0) = 0$$

thus $x + cy \in \text{Null}(A)$. Closure of addition for $\text{Null}(A)$ follows from $c = 1$ and closure of scalar multiplication follows from $x = 0$ in the just completed calculation. \square

Sometimes it's easier to check both scalar multiplication and addition at once. It saves some writing. If you don't understand it then don't use the trick I just used, we should understand what we are doing.

Example 5.2.10. Let $W = \{A \in \mathbb{R}^{n \times n} \mid A^T = A\}$. This is the set of **symmetric matrices**, it is nonempty since $I^T = I$ (of course there are many other examples, we only need one to show it's nonempty). Let $A, B \in W$ and suppose $c \in \mathbb{R}$ then

$$\begin{aligned} (A + B)^T &= A^T + B^T && \text{prop. of transpose} \\ &= A + B && \text{since } A, B \in W \end{aligned}$$

thus $A + B \in W$ and we find W is closed under addition. Likewise let $A \in W$ and $c \in \mathbb{R}$,

$$\begin{aligned} (cA)^T &= cA^T && \text{prop. of transpose} \\ &= cA && \text{since } A \in W \end{aligned}$$

thus $cA \in W$ and we find W is closed under scalar multiplication. Therefore, by the subspace test Theorem 5.2.6, $W \leq \mathbb{R}^{n \times n}$.

Example 5.2.11. Let $W = \{f \in \mathcal{F}(\mathbb{R}) \mid \int_{-1}^1 f(x) dx = 0\}$. Notice the zero function $0(x) = 0$ is in W since $\int_{-1}^1 0 dx = 0$. Let $f, g \in W$, use linearity property of the definite integral to calculate

$$\int_{-1}^1 (f(x) + g(x)) dx = \int_{-1}^1 f(x) dx + \int_{-1}^1 g(x) dx = 0 + 0 = 0$$

thus $f + g \in W$. Likewise, if $c \in \mathbb{R}$ and $f \in W$ then

$$\int_{-1}^1 cf(x) dx = c \int_{-1}^1 f(x) dx = c(0) = 0$$

thus $cf \in W$ and by subspace test Theorem 5.2.6 $W \leq \mathcal{F}(\mathbb{R})$.

5.3 spanning sets and subspaces

The expression $x + cy$ is a "linear combination" of x and y . Subspaces must keep linear combinations of subspace vectors from escaping the subspace. We defined linear combinations in a previous chapter (see 2.2.7). Can we use linear combinations to form a subspace?

Theorem 5.3.1.

Let V be a vector space which contains vectors v_1, v_2, \dots, v_k then

1. the set of all linear combinations of v_1, v_2, \dots, v_k forms a subspace of V , call it W_o
2. W_o is the smallest subspace of V which contains v_1, v_2, \dots, v_k . Any other subspace which contains v_1, v_2, \dots, v_k also contains W_o .

Proof: Define $W_o = \{c_1v_1 + c_2v_2 + \dots + c_kv_k \mid c_i \in \mathbb{R} \text{ for } i = 1, 2, \dots, k\}$. Notice $0 \cdot v_1 = 0$ hence $0 \in W_o$. Suppose that $x, y \in W_o$ then there exist constants c_i and b_i such that

$$x = c_1v_1 + c_2v_2 + \dots + c_kv_k \quad y = b_1v_1 + b_2v_2 + \dots + b_kv_k$$

Consider the sum of x and y ,

$$\begin{aligned} x + y &= c_1v_1 + c_2v_2 + \dots + c_kv_k + b_1v_1 + b_2v_2 + \dots + b_kv_k \\ &= (c_1 + b_1)v_1 + (c_2 + b_2)v_2 + \dots + (c_k + b_k)v_k \end{aligned}$$

thus $x + y \in W_o$ for all $x, y \in W_o$. Let $a \in \mathbb{R}$ and observe

$$ax = a(c_1v_1 + c_2v_2 + \dots + c_kv_k) = ac_1v_1 + ac_2v_2 + \dots + ac_kv_k$$

thus $cx \in W_o$ for all $x \in W_o$ and $c \in \mathbb{R}$. Thus by the subspace test theorem we find $W_o \leq V$.

To prove (2.) we suppose R is any subspace of V which contains v_1, v_2, \dots, v_k . By definition R is closed under scalar multiplication and vector addition thus all linear combinations of v_1, v_2, \dots, v_k must be in R hence $W_o \subseteq R$. Finally, it is clear that $v_1, v_2, \dots, v_k \in W_o$ since $v_1 = 1v_1 + 0v_2 + \dots + 0v_k$ and $v_2 = 0v_1 + 1v_2 + \dots + 0v_k$ and so forth. \square

Definition 5.3.2.

Let $S = \{v_1, v_2, \dots, v_k\}$ be a finite set of vectors in a vector space V then $\text{span}(S)$ is defined to be the sset of all linear combinations of S :

$$\text{span}\{v_1, v_2, \dots, v_k\} = \left\{ \sum_{i=1}^k c_i v_i \mid c_i \in \mathbb{R} \text{ for } i = 1, 2, \dots, k \right\}$$

If $W = \text{span}(S)$ then we say that S is a **generating set** for W .

In view of Theorem 5.3.1 the definition above is equivalent to defining $\text{span}(S)$ to be the smallest subspace which contains S .

Example 5.3.3. *Spans help us understand three dimensional geometry:*

1. a line through the origin is spanned by its direction vector.
2. a plane through the origin is spanned by any two non-parallel vectors that lie in that plane.
3. three dimensional space is spanned by three non-coplanar vectors. For example, $\hat{i}, \hat{j}, \hat{k}$ span \mathbb{R}^3 .

Example 5.3.4. *Proposition 2.2.8 explained how \mathbb{R}^n was spanned by the standard basis; $\mathbb{R}^n = \text{span}\{e_i\}_{i=1}^n$. Likewise, Proposition 3.7.2 showed the $m \times n$ matrix units E_{ij} spanned the set of all $m \times n$ matrices; $\mathbb{R}^{m \times n} = \text{span}\{E_{ij}\}_{i,j=1}^n$.*

Example 5.3.5. *Let $S = \{1, x, x^2, \dots, x^n\}$ then $\text{span}(S) = P_n$. For example,*

$$\text{span}\{1, x, x^2\} = \{ax^2 + bx + c \mid a, b, c \in \mathbb{R}\} = P_2$$

The set of all polynomials is spanned by $\{1, x, x^2, x^3, \dots\}$. We are primarily interested in the span of finite sets however this case is worth mentioning.

The following definition explains what is meant by the span of an infinite set. In words, the span is the set of all finite linear combinations in the possibly infinite set. (I used this definition implicitly in the preceding example)

Definition 5.3.6.

Let S be a set of vectors. We say that S is **spanned** by a set of vectors B iff each $v \in S$ is a finite linear combination of the vectors in B . Moreover, given vectors v_1, v_2, \dots, v_k of the same type,

$$\text{span}\{v_1, v_2, \dots, v_k\} = \{w \mid \exists c_i \text{ such that } w = c_1 v_1 + c_2 v_2 + \dots + c_k v_k\}$$

Example 5.3.7. Let $W = \{[s+t, 2s+t, 3s+t]^T \mid s, t \in \mathbb{R}\}$. We can show W is a subspace of $\mathbb{R}^{3 \times 1}$. What is a generating set of W ? Let $w \in W$ then by definition there exist $s, t \in \mathbb{R}$ such that

$$w = \begin{bmatrix} s+t \\ 2s+t \\ 3s+t \end{bmatrix} = s \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} + t \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

Thus $w \in \text{span}\{[1, 2, 3]^T, [1, 1, 1]^T\}$ and it follows $W \subseteq \text{span}\{[1, 2, 3]^T, [1, 1, 1]^T\}$. Conversely, if $y \in \text{span}\{[1, 2, 3]^T, [1, 1, 1]^T\}$ then there exist $c_1, c_2 \in \mathbb{R}$ such that $y = c_1[1, 2, 3]^T + c_2[1, 1, 1]^T$. But then $y = [c_1 + c_2, 2c_1 + c_2, 3c_1 + c_2]^T$ so it is clear $y \in W$, therefore $\text{span}\{[1, 2, 3]^T, [1, 1, 1]^T\} \subseteq W$. It follows that $W = \text{span}\{[1, 2, 3]^T, [1, 1, 1]^T\}$. Finally, Theorem 5.3.1 guarantees that $W \leq \mathbb{R}^{3 \times 1}$.

The lesson of the last example is that we can show a particular space is a subspace by finding its generating set. Theorem 5.3.1 tells us that any set generated by a span is a subspace. This test is only convenient for subspaces which are defined as some sort of span. In that case we can immediately conclude the subset is in fact a subspace.

Example 5.3.8. Suppose $a, b, c \in \mathbb{R}$ and $a \neq 0$. Consider the differential equation $ay'' + by' + cy = 0$. There is a theorem in the study of differential equations which states **every** solution can be written as a linear combination of a pair of special solutions y_1, y_2 ; we say $y = c_1y_1 + c_2y_2$ is the "general solution" in the terminology of Math 334. In other words, there exist solutions y_1, y_2 such that the solution set S of $ay'' + by' + cy = 0$ is

$$S = \text{span}\{y_1, y_2\}.$$

Since S is a span it is clear that $S \leq \mathcal{F}(\mathbb{R})$.

Example 5.3.9. Suppose $L = P(D)$ where $D = d/dx$ and P is a polynomial with real coefficients. This makes L a smooth operator on the space of smooth functions. Suppose $\deg(P) = n$, a theorem in differential equations states that there exist solutions y_1, y_2, \dots, y_n of $L[y] = 0$ such that **every** solution of $L[y] = 0$ can be written in the form $y = c_1y_1 + c_2y_2 + \dots + c_ny_n$ for constants $c_1, c_2, \dots, c_n \in \mathbb{R}$. In other words, the solution set S of $L[y] = 0$ is formed from a span:

$$S = \text{span}\{y_1, y_2, \dots, y_n\}.$$

Notice the last example is a subcase of this example. Simply set $L = aD^2 + bD + c$.

It is entirely likely that the abstraction of the last two examples has confounded the majority of the audience for these notes. Let me give a couple specific examples in the same vein.

Example 5.3.10. Consider $y' = y$. Or, taking t as the independent variable, $\frac{dy}{dt} = y$. Separation of variables (that you are required to know from calculus II) shows $\frac{dy}{y} = dt$ hence $\ln|y| = t + c$. It follows that $y = \pm e^c e^t$. Note $y = 0$ is also a solution of $y' = y$. In total, we find solutions of the form $y = c_1 e^t$. The solution set of this differential equation is a span; $S = \text{span}\{e^t\} \leq \mathcal{F}(\mathbb{R})$.

Example 5.3.11. Consider $y'' - y = 0$. I invite the reader to verify that $y_1 = \cosh(t)$ and $y_2 = \sinh(t)$ are solutions. The solution set is $S = \text{span}\{y_1, y_2\} \leq \mathcal{F}(\mathbb{R})$.

Example 5.3.12. Consider $y'' + y = 0$. I invite the reader to verify that $y_1 = \cos(t)$ and $y_2 = \sin(t)$ are solutions. The solution set is $S = \text{span}\{y_1, y_2\} \leq \mathcal{F}(\mathbb{R})$. Physically, this could represent Newton's equation for a spring with mass $m = 1$ and stiffness $k = 1$, the set of all possible physical motions forms a linear subspace of function space.

Example 5.3.13. Consider, $y''' = 0$. Integrate both sides to find $y'' = c_1$. Integrate again to find $y' = c_1 t + c_2$. Integrate once more, $y = c_1 \frac{1}{2} t^2 + c_2 t + c_3$. The general solution of $y''' = 0$ is a subspace S of function space:

$$S = \text{span}\left\{\frac{1}{2}t^2, t, 1\right\} \leq \mathcal{F}(\mathbb{R})$$

Physically, we usually have the situation $c_1 = g$.

Examples 5.3.10 and 5.3.13 are fair game for test, quizzes etc... they only assume prerequisite knowledge plus linear algebra. In contrast, I don't expect you can find y_1, y_2 as in Examples 5.3.11 and 5.3.12 since Math 334 is not a prerequisite.

Example 5.3.14. Let $A \in \mathbb{R}^{m \times n}$. Define the **column space** of A as the span of the columns of A :

$$\text{Col}(A) = \text{span}\{\text{col}_j(A) \mid j = 1, 2, \dots, n\}$$

this is clearly a subspace of $\mathbb{R}^{n \times 1}$ since it is constructed as a span of vectors in E_{11} and E_{22} . We also can define row space as the span of the rows:

$$\text{Row}(A) = \text{span}\{\text{row}_i(A) \mid i = 1, 2, \dots, m\}$$

this is clearly a subspace of $\mathbb{R}^{1 \times m}$ since it is formed as a span of vectors. Since the columns of A^T are the rows of A and the rows of A^T are the columns of A we can conclude that $\text{Col}(A^T) = \text{Row}(A)$ and $\text{Row}(A^T) = \text{Col}(A)$.

I would remind the reader we have seen examples with more bite for the case $V = \mathbb{R}^n$ in the vector chapter. We began with \mathbb{R}^n because it is a nice concrete case from which everything else finite dimensional flows.

Remark 5.3.15.

If we are given $B = \{b_1, b_2, \dots, b_k\} \subset \mathbb{R}^n$ and $T = \{w_1, w_2, \dots, w_r\} \subset \mathbb{R}^n$ and we wish to determine if $T \subset \text{span}(B)$ then we can answer the question by examining if $[b_1 | b_2 | \dots | b_k]x = w_j$ has a solution for each $j = 1, 2, \dots, r$. Or we could make use of Proposition 3.6.1 and solve it in one sweeping matrix calculation;

$$\text{rref}[b_1 | b_2 | \dots | b_k | w_1 | w_2 | \dots | w_r]$$

If there is a row with zeros in the first k -columns and a nonzero entry in the last r -columns then this means that at least one vector w_k is not in the span of B (moreover, the vector not in the span corresponds to the nonzero entry(s)). Otherwise, each vector is in the span of B and we can read the precise linear combination from the matrix. I will illustrate this in the example that follows.

Example 5.3.16. Let $W = \text{span}\{e_1 + e_2, e_2 + e_3, e_1 - e_3\}$ and suppose $T = \{e_1, e_2, e_3 - e_1\}$. Is $T \leq W$? If not, which vectors in T are not in W ? Consider,

$$\begin{aligned}
 [e_1 + e_1 | e_2 + e_3 | e_1 - e_3 | e_1 | e_2 | e_3 - e_1] &= \left[\begin{array}{ccc|ccc} 1 & 0 & 1 & 1 & 0 & -1 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & -1 & 0 & 0 & 1 \end{array} \right] \xrightarrow{r_2 - r_1 \rightarrow r_2} \\
 &\left[\begin{array}{ccc|ccc} 1 & 0 & 1 & 1 & 0 & -1 \\ 0 & 1 & -1 & -1 & 1 & 1 \\ 0 & 1 & -1 & 0 & 0 & 1 \end{array} \right] \xrightarrow{r_3 - r_2 \rightarrow r_3} \\
 &\left[\begin{array}{ccc|ccc} 1 & 0 & 1 & 1 & 0 & -1 \\ 0 & 1 & -1 & -1 & 1 & 1 \\ 0 & 0 & 0 & 1 & -1 & 0 \end{array} \right] \xrightarrow{\begin{array}{l} r_2 + r_3 \rightarrow r_2 \\ r_1 - r_3 \rightarrow r_1 \end{array}} \\
 &\left[\begin{array}{ccc|ccc} 1 & 0 & 1 & 0 & 1 & -1 \\ 0 & 1 & -1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & -1 & 0 \end{array} \right]
 \end{aligned}$$

Let me summarize the calculation:

$$\text{rref}[e_1 + e_2 | e_2 + e_3 | e_1 - e_3 | e_1 | e_2 | e_3 - e_1] = \left[\begin{array}{ccc|ccc} 1 & 0 & 1 & 0 & 1 & -1 \\ 0 & 1 & -1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & -1 & 0 \end{array} \right]$$

We deduce that e_1 and e_2 are not in W . However, $e_1 - e_3 \in W$ and we can read from the matrix $-(e_1 + e_2) + (e_2 + e_3) = e_3 - e_1$. I added the double vertical bar for book-keeping purposes, as usual the vertical bars are just to aid the reader in parsing the matrix.

The tricks we've developed in these last few examples really only work for vectors in \mathbb{R}^n . If we have abstract vectors, or even just row vectors, then we'll need to deal with spanning questions by other methods. However, once we have the idea of *coordinates* ironed out then we can use the tricks on the coordinate vectors then push back the result to the world of abstract vectors. For now we'll just confront each question by brute force.

Example 5.3.17. Is $E_{11} \in \text{span}\{E_{12} + 2E_{11}, E_{12} - E_{11}\}$? Assume $E_{ij} \in \mathbb{R}^{2 \times 2}$ for all i, j . We seek to find solutions of

$$E_{11} = a(E_{12} + 2E_{11}) + b(E_{12} - E_{11})$$

in explicit matrix form the equation above reads:

$$\begin{aligned} \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} &= a \left(\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix} \right) + b \left(\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} -1 & 0 \\ 0 & 0 \end{bmatrix} \right) \\ &= \begin{bmatrix} 2a & a \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} -b & b \\ 0 & 0 \end{bmatrix} \\ &= \begin{bmatrix} 2a - b & a + b \\ 0 & 0 \end{bmatrix} \end{aligned}$$

thus $1 = 2a - b$ and $0 = a + b$. Substitute $a = -b$ to find $1 = 3a$ hence $a = \frac{1}{3}$ and $b = -\frac{1}{3}$. Indeed,

$$\frac{1}{3}(E_{12} + 2E_{11}) - \frac{1}{3}(E_{12} - E_{11}) = \frac{2}{3}E_{11} + \frac{1}{3}E_{11} = E_{11}.$$

Therefore, $E_{11} \in \text{span}\{E_{12} + 2E_{11}, E_{12} - E_{11}\}$.

Example 5.3.18. Find a generating set for the set of symmetric 2×2 matrices. That is find a set S of matrices such that $\text{span}(S) = \{A \in \mathbb{R}^{2 \times 2} \mid A^T = A\} = W$. There are many approaches, but I find it most natural to begin by studying the condition which defines W . Let $A \in W$ and

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \Rightarrow \begin{bmatrix} a & c \\ b & d \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

this means we need $b = c$ but we find no particular condition on a or d . Notice $A \in W$ implies

$$A = \begin{bmatrix} a & b \\ b & d \end{bmatrix} = a \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + b \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + d \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} = aE_{11} + b(E_{12} + E_{21}) + dE_{22}$$

Thus $A \in W$ implies $A \in \text{span}\{E_{11}, E_{12} + E_{21}, E_{22}\}$, hence $W \subseteq \text{span}\{E_{11}, E_{12} + E_{21}, E_{22}\}$. Conversely, if $B \in \text{span}\{E_{11}, E_{12} + E_{21}, E_{22}\}$ then there exist $c_1, c_2, c_3 \in \mathbb{R}$ such that

$$B = c_1E_{11} + c_2(E_{12} + E_{21}) + c_3E_{22}$$

but this means

$$B = \begin{bmatrix} c_1 & c_2 \\ c_2 & c_3 \end{bmatrix}$$

so B is symmetric and it follows $\text{span}\{E_{11}, E_{12} + E_{21}, E_{22}\} \subseteq W$. Consequently $W = \text{span}\{E_{11}, E_{12} + E_{21}, E_{22}\}$ and the set $\{E_{11}, E_{12} + E_{21}, E_{22}\}$ generates W . This is not unique, there are many other sets which also generate W . For example, if we took $\tilde{S} = \{E_{11}, E_{12} + E_{21}, E_{22}, E_{11} + E_{22}\}$ then the span of \tilde{S} would still work out to W .

Theorem 5.3.19.

If $S = \{s_1, s_2, \dots, s_k\}$ and $T = \{t_1, t_2, \dots, t_r\}$ are subsets of a vector space V then $\text{span}(S) = \text{span}(T)$ if and only if every vector in S is a linear combination of vectors in T and every vector in T is a linear combination of vectors in S .

Proof: (\Rightarrow) Assume $\text{span}(S) = \text{span}(T)$. If $v \in S$ then $v \in \text{span}(S)$ hence $v \in \text{span}(T)$ and it follows that v is a linear combination of vectors in T . If $w \in T$ then $w \in \text{span}(T)$ hence $w \in \text{span}(S)$ and by definition of the $\text{span}(S)$ we find w is a linear combination of vectors in S .

(\Leftarrow) Assume every vector in S is a linear combination of vectors in T and every vector in T is a linear combination of vectors in S . Suppose $v \in \text{Span}(S)$ then v is a linear combination of vectors in S , say

$$v = c_1 s_1 + c_2 s_2 + \dots + c_k s_k.$$

Furthermore, each vector in S is a linear combination of vectors in T by assumption so there exist constants d_{ij} such that

$$s_i = d_{i1} t_1 + d_{i2} t_2 + \dots + d_{ir} t_r$$

for each $i = 1, 2, \dots, k$. Thus,

$$\begin{aligned} v &= c_1 s_1 + c_2 s_2 + \dots + c_k s_k. \\ &= c_1 (d_{11} t_1 + d_{12} t_2 + \dots + d_{1r} t_r) + c_2 (d_{21} t_1 + d_{22} t_2 + \dots + d_{2r} t_r) + \\ &\quad \dots + c_k (d_{k1} t_1 + d_{k2} t_2 + \dots + d_{kr} t_r) \\ &= (c_1 d_{11} + c_2 d_{21} + \dots + c_k d_{k1}) t_1 + (c_1 d_{12} + c_2 d_{22} + \dots + c_k d_{k2}) t_2 + \\ &\quad \dots + (c_1 d_{1r} + c_2 d_{2r} + \dots + c_k d_{kr}) t_r \end{aligned}$$

thus v is a linear combination of vectors in T , in other words $v \in \text{span}(T)$ and we find $\text{span}(S) \subseteq \text{span}(T)$. Notice, we just proved that a linear combination of linear combinations is again a linear combination. Almost the same argument shows $\text{span}(T) \subseteq \text{span}(S)$ hence $\text{span}(S) = \text{span}(T)$. \square .

5.4 linear independence

We have seen a variety of generating sets in the preceding section. In the last example I noted that if we added an additional vector $E_{11} + E_{22}$ then the same span would be created. The vector $E_{11} + E_{22}$ is **redundant** since we already had E_{11} and E_{22} . In particular, $E_{11} + E_{22}$ is a linear combination of E_{11} and E_{22} so adding it will not change the span. How can we decide if a vector is absolutely necessary for a span? In other words, if we want to span a subspace W then how do we find a **minimal spanning set**? We want a set of vectors which does not have any linear dependencies. For example, $\hat{i}, \hat{j}, \hat{k}$ spans \mathbb{R}^3 however if we took any one of these away we would only generate a plane. We say such vectors are linearly independent. Let me be precise:

Definition 5.4.1.

If a vector v_k can be written as a linear combination of vectors $\{v_1, v_2, \dots, v_{k-1}\}$ then we say that the vectors $\{v_1, v_2, \dots, v_{k-1}, v_k\}$ are **linearly dependent**.
If the vectors $\{v_1, v_2, \dots, v_{k-1}, v_k\}$ are not linear dependent then they are said to be **linearly independent**.

Example 5.4.2. Let $v = [1 \ 2 \ 3]^T$ and $w = [2 \ 4 \ 6]^T$. Clearly v, w are linearly dependent since $w = 2v$.

I often quote the following proposition as the definition of linear independence, it is an equivalent statement and as such can be used as the definition. If this was our definition then our definition would become a proposition. Math always has a certain amount of this sort of ambiguity.

Proposition 5.4.3.

Let $v_1, v_2, \dots, v_k \in V$ a vector space. The set of vectors $\{v_1, v_2, \dots, v_k\}$ is linearly independent iff

$$c_1v_1 + c_2v_2 + \dots + c_kv_k = 0 \Rightarrow c_1 = c_2 = \dots = c_k = 0.$$

Proof: (\Rightarrow) Suppose $\{v_1, v_2, \dots, v_k\}$ is linearly independent. Assume that there exist constants c_1, c_2, \dots, c_k such that

$$c_1v_1 + c_2v_2 + \dots + c_kv_k = 0$$

and at least one constant, say c_j , is nonzero. Then we can divide by c_j to obtain

$$\frac{c_1}{c_j}v_1 + \frac{c_2}{c_j}v_2 + \dots + v_j + \dots + \frac{c_k}{c_j}v_k = 0$$

solve for v_j , (we mean for \hat{v}_j to denote the deletion of v_j from the list)

$$v_j = -\frac{c_1}{c_j}v_1 - \frac{c_2}{c_j}v_2 - \dots - \hat{v}_j - \dots - \frac{c_k}{c_j}v_k$$

but this means that v_j linearly depends on the other vectors hence $\{v_1, v_2, \dots, v_k\}$ is linearly dependent. This is a contradiction, therefore $c_j = 0$. Note j was arbitrary so we may conclude $c_j = 0$

for all j . Therefore, $c_1v_1 + c_2v_2 + \cdots + c_kv_k = 0 \Rightarrow c_1 = c_2 = \cdots = c_k = 0$.

Proof: (\Leftarrow) Assume that

$$c_1v_1 + c_2v_2 + \cdots + c_kv_k = 0 \Rightarrow c_1 = c_2 = \cdots = c_k = 0.$$

If $v_j = b_1v_1 + b_2v_2 + \cdots + \widehat{b_jv_j} + \cdots + b_kv_k$ then $b_1v_1 + b_2v_2 + \cdots + b_jv_j + \cdots + b_kv_k = 0$ where $b_j = -1$, this is a contradiction. Therefore, for each j , v_j is not a linear combination of the other vectors. Consequently, $\{v_1, v_2, \dots, v_k\}$ is linearly independent.

Proposition 5.4.4.

S is a linearly independent set of vectors iff for all $v_1, v_2, \dots, v_k \in S$,

$$a_1v_1 + a_2v_2 + \cdots + a_kv_k = b_1v_1 + b_2v_2 + \cdots + b_kv_k$$

implies $a_i = b_i$ for each $i = 1, 2, \dots, k$. In other words, we can equate coefficients of linearly independent vectors. And, conversely if a set of vectors allows for equating coefficients then it is linearly independent.

Proof: see the Problem Set. This is important, you need to prove it for yourself. This is yet another equivalent definition of linear independence, as such I will at times say we can equate coefficients since the vectors are linearly independent. \square

Proposition 5.4.5.

If S is a finite set of vectors which contains the zero vector then S is linearly dependent.

Proof: Let $\{\vec{0}, v_2, \dots, v_k\} = S$ and observe that

$$1\vec{0} + 0v_2 + \cdots + 0v_k = 0$$

Thus $c_1\vec{0} + c_2v_2 + \cdots + c_kv_k = 0$ does not imply $c_1 = 0$ hence the set of vectors is not linearly independent. Thus S is linearly dependent. \square

Proposition 5.4.6.

Let v and w be nonzero vectors.

$$v, w \text{ are linearly dependent} \Leftrightarrow \exists k \neq 0 \in \mathbb{R} \text{ such that } v = kw.$$

Proof: Suppose v, w are linearly dependent then there exist constants c_1, c_2 , not all zero, such that $c_1v + c_2w = 0$. Suppose that $c_1 = 0$ then $c_2w = 0$ hence $c_2 = 0$ or $w = 0$ by (4.) of Theorem 5.1.8. But this is a contradiction since v, w are nonzero and at least one of c_1, c_2 must be nonzero. Therefore, $c_1 \neq 0$. Likewise, if $c_2 = 0$ we find a similar contradiction. Hence c_1, c_2 are both nonzero and we calculate $v = (-c_2/c_1)w$, identify that $k = -c_2/c_1$. \square

Remark 5.4.7.

We should keep in mind that in the abstract context statements such as "v and w go in the same direction" or "u is contained in the plane spanned by v and w" are not statements about ordinary three dimensional geometry. Moreover, you **cannot** write that $u, v, w \in \mathbb{R}^n$ unless you happen to be working with that rather special vector space. These "vectors" could be matrices, polynomials or even operators. All of this said, we will find a way to correctly think of an abstract vector space V as another version of \mathbb{R}^n . We'll see how V and \mathbb{R}^n correspond, we will not be so careless as to say they are equal.

Recall that we used Proposition 2.5.8 in Examples 2.5.10, 2.5.11, 2.5.12 and 2.5.13 to ascertain the linear independence of certain sets of vectors. If you pay particular attention to those examples you may have picked up on a pattern. The columns of the $rref[v_1|v_2|\cdots|v_k]$ depend on each other in the same way that the vectors v_1, v_2, \dots, v_k depend on each other. These provide examples of the so-called "**column correspondence property**". In a nutshell, the property says you can read the linear dependencies right off the $rref[v_1|v_2|\cdots|v_k]$.

Proposition 5.4.8. *Column Correspondence Property (CCP)*

Let $A = [col_1(A)|\cdots|col_n(A)] \in \mathbb{R}^{m \times n}$ and $R = rref[A] = [col_1(R)|\cdots|col_n(R)]$. There exist constants c_1, c_2, \dots, c_k such that $c_1 col_1(A) + c_2 col_2(A) + \cdots + c_k col_k(A) = 0$ if and only if $c_1 col_1(R) + c_2 col_2(R) + \cdots + c_k col_k(R) = 0$. If $col_j(rref[A])$ is a linear combination of other columns of $rref[A]$ then $col_j(A)$ is likewise the same linear combination of columns of A .

We prepare for the proof of the Proposition by establishing a useful Lemma.

Lemma 5.4.9.

Let $A \in \mathbb{R}^{m \times n}$ then there exists an invertible matrix E such that $col_j(rref(A)) = Ecol_j(A)$ for all $j = 1, 2, \dots, n$.

Proof of Lemma: Recall that there exist elementary matrices E_1, E_2, \dots, E_r such that $A = E_1 E_2 \cdots E_r rref(A) = E^{-1} rref(A)$ where I have defined $E^{-1} = E_1 E_2 \cdots E_r$ for convenience. Recall the concatenation proposition: $X[b_1|b_2|\cdots|b_k] = [Xb_1|Xb_2|\cdots|Xb_k]$. We can unravel the Gaussian elimination in the same way,

$$\begin{aligned} EA &= E[col_1(A)|col_2(A)|\cdots|col_n(A)] \\ &= [Ecol_1(A)|Ecol_2(A)|\cdots|Ecol_n(A)] \end{aligned}$$

Observe that $EA = rref(A)$ hence we find the above equation says $col_j(rref(A)) = Ecol_j(A)$ for all j . \square

Proof of Proposition: Suppose that there exist constants c_1, c_2, \dots, c_k such that $c_1 col_1(A) + c_2 col_2(A) + \cdots + c_k col_k(A) = 0$. By the Lemma we know there exists E such that $col_j(rref(A)) = Ecol_j(A)$. Multiply linear combination by E to find:

$$c_1 Ecol_1(A) + c_2 Ecol_2(A) + \cdots + c_k Ecol_k(A) = 0$$

which yields

$$c_1 \text{col}_1(\text{rref}(A)) + c_2 \text{col}_2(\text{rref}(A)) + \cdots + c_k \text{col}_k(\text{rref}(A)) = 0.$$

Likewise, if we are given a linear combination of columns of $\text{rref}(A)$ we can multiply by E^{-1} to recover the same linear combination of columns of A . \square

Example 5.4.10. *I will likely use the abbreviation "CCP" for column correspondence property. We could have deduced all the linear dependencies via the CCP in Examples 2.5.10, 2.5.12 and 2.5.13. We found in 2.5.10 that*

$$\text{rref}[v_1|v_2|v_3] = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix}.$$

Obviously $\text{col}_3(R) = \text{col}_1(R) + \text{col}_2(R)$ hence by CCP $v_3 = v_1 + v_2$.

We found in 2.5.12 that

$$\text{rref}[v_1|v_2|v_3] = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

By inspection, $\text{col}_3(R) = \text{col}_2(R) - \text{col}_1(R)$ hence by CCP $v_3 = v_2 - v_1$.

We found in 2.5.13 that

$$\text{rref}[v_1|v_2|v_3|v_4] = \begin{bmatrix} 1 & 0 & 1 & -1 \\ 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

By inspection, $\text{col}_3(R) = \text{col}_1(R) + \text{col}_2(R)$ hence by CCP $v_3 = v_1 + v_2$. Likewise by inspection, $\text{col}_4(R) = \text{col}_2(R) - \text{col}_1(R)$ hence by CCP $v_4 = v_2 - v_1$.

You should notice that the CCP saves us the trouble of expressing how the constants c_i are related. If we are only interested in how the vectors are related the CCP gets straight to the point quicker. We should pause and notice another pattern here while were thinking about these things.

Proposition 5.4.11.

The non-pivot columns of a matrix can be written as linear combinations of the pivot columns and the pivot columns of the matrix are linearly independent.

Proof: Let A be a matrix. Notice the Proposition is clearly true for $\text{rref}(A)$. Hence, using Lemma 5.4.9 we find the same is true for the matrix A . \square

Proposition 5.4.12.

The rows of a matrix A can be written as linear combinations of the transposes of pivot columns of A^T , and the rows which are transposes of the pivot columns of A^T are linearly independent.

Proof: Let A be a matrix and A^T its transpose. Apply Proposition 5.4.8 to A^T to find pivot columns which we denote by $\text{col}_{i_j}(A^T)$ for $j = 1, 2, \dots, k$. These columns are linearly independent and they span $\text{Col}(A^T)$. Suppose,

$$c_1 \text{row}_{i_1}(A) + c_2 \text{row}_{i_2}(A) + \dots + c_k \text{row}_{i_k}(A) = 0.$$

Take the transpose of the equation above, use Proposition 3.9.3 to simplify:

$$c_1 (\text{row}_{i_1}(A))^T + c_2 (\text{row}_{i_2}(A))^T + \dots + c_k (\text{row}_{i_k}(A))^T = 0.$$

Recall $(\text{row}_j(A))^T = \text{col}_j(A^T)$ thus,

$$c_1 \text{col}_{i_1}(A^T) + c_2 \text{col}_{i_2}(A^T) + \dots + c_k \text{col}_{i_k}(A^T) = 0.$$

hence $c_1 = c_2 = \dots = c_k = 0$ as the pivot columns of A^T are linearly independent. This shows the corresponding rows of A are likewise linearly independent. The proof that these same rows span $\text{Row}(A)$ is similar. \square

5.4.1 linear independence in abstract vector spaces

Given a set of vectors in \mathbb{R}^n the question of LI is elegantly answered by the CCP. In this section we leave the comfort zone and study LI in abstract vector spaces. For now we only have brute force at our disposal. In other words, I'll argue directly from the definition without the aid of the CCP from the outset.

Example 5.4.13. Suppose $f(x) = \cos(x)$ and $g(x) = \sin(x)$ and define $S = \{f, g\}$. Is S linearly independent with respect to the standard vector space structure on $\mathcal{F}(\mathbb{R})$? Let $c_1, c_2 \in \mathbb{R}$ and assume that

$$c_1 f + c_2 g = 0.$$

It follows that $c_1 f(x) + c_2 g(x) = 0$ for each $x \in \mathbb{R}$. In particular,

$$c_1 \cos(x) + c_2 \sin(x) = 0$$

for each $x \in \mathbb{R}$. Let $x = 0$ and we get $c_1 \cos(0) + c_2 \sin(0) = 0$ thus $c_1 = 0$. Likewise, let $x = \pi/2$ to obtain $c_1 \cos(\pi/2) + c_2 \sin(\pi/2) = 0 + c_2 = 0$ hence $c_2 = 0$. We have shown that $c_1 f + c_2 g = 0$ implies $c_1 = c_2 = 0$ thus $S = \{f, g\}$ is a linearly independent set.

Example 5.4.14. Let $f_n(t) = t^n$ for $n = 0, 1, 2, \dots$. Suppose $S = \{f_0, f_1, \dots, f_n\}$. Show S is a linearly independent subset of function space. Assume $c_0, c_1, \dots, c_n \in \mathbb{R}$ and

$$c_0 f_0 + c_1 f_1 + c_2 f_2 + \dots + c_n f_n = 0. \quad \star$$

I usually skip the expression above, but I'm including this extra step to emphasize the distinction between the function and its formula. The \star equation is a function equation, it implies

$$c_0 + c_1 t + c_2 t^2 + \dots + c_n t^n = 0 \quad \star \star$$

for all $t \in \mathbb{R}$. Evaluate $\star\star$ at $t = 0$ to obtain $c_0 = 0$. Differentiate \star^2 and find

$$c_1 + 2c_2t + \cdots + nc_nt^{n-1} = 0 \quad \star^3$$

Evaluate \star^3 at $t = 0$ to obtain $c_1 = 0$. If we continue to differentiate and evaluate we will similarly obtain $c_2 = 0$, $c_3 = 0$ and so forth all the way up to $c_n = 0$. Therefore, \star implies $c_0 = c_1 = \cdots = c_n = 0$.

Linear dependence in function space is sometimes a source of confusion for students. The idea of evaluation doesn't help in the same way as it just has in the two examples above.

Example 5.4.15. Let $f(t) = t - 1$ and $g(t) = t + t^2$ is f linearly dependent on g ? A common mistake is to say something like $f(1) = 1 - 1 = 0$ so $\{f, g\}$ is linearly independent since it contains zero. Why is this wrong? The reason is that we have confused the value of the function with the function itself. If $f(t) = 0$ for all $t \in \mathbb{R}$ then f is the zero function which is the zero vector in function space. Many functions will be zero at a point but that doesn't make them the zero function. To prove linear dependence we must show that there exists $k \in \mathbb{R}$ such that $f = kg$, but this really means that $f(t) = kg(t)$ for all $t \in \mathbb{R}$ in the current context. I leave it to the reader to prove that $\{f, g\}$ is in fact LI. You can evaluate at $t = 1$ and $t = 0$ to obtain equations for c_1, c_2 which have a unique solution of $c_1 = c_2 = 0$.

Example 5.4.16. Let $f(t) = t^2 - 1$, $g(t) = t^2 + 1$ and $h(t) = 4t^2$. Suppose

$$c_1(t^2 - 1) + c_2(t^2 + 1) + c_3(4t^2) = 0 \quad \star$$

A little algebra reveals,

$$(c_1 + c_2 + 4c_3)t^2 - (c_1 - c_2)1 = 0$$

Using linear independence of t^2 and 1 we find

$$c_1 + c_2 + 4c_3 = 0 \quad \text{and} \quad c_1 - c_2 = 0$$

We find infinitely many solutions,

$$c_1 = c_2 \quad \text{and} \quad c_3 = -\frac{1}{4}(c_1 + c_2) = -\frac{1}{2}c_2$$

Therefore, \star allows nontrivial solutions. Take $c_2 = 1$,

$$1(t^2 - 1) + 1(t^2 + 1) - \frac{1}{2}(4t^2) = 0.$$

We can write one of these functions as a linear combination of the other two,

$$f = -g + \frac{1}{2}h.$$

Once we get past the formalities of the particular vector space structure it always comes back to solving systems of linear equations.

5.5 bases and dimension

We have seen that linear combinations can generate vector spaces. We have also seen that sometimes we can remove a vector from the generating set and still generate the whole vector space. For example,

$$\text{span}\{e_1, e_2, e_1 + e_2\} = \mathbb{R}^{2 \times 1}$$

and we can remove any one of these vector and still span $\mathbb{R}^{2 \times 1}$,

$$\text{span}\{e_1, e_2\} = \text{span}\{e_1, e_1 + e_2\} = \text{span}\{e_2, e_1 + e_2\} = \mathbb{R}^{2 \times 1}$$

However, if we remove another vector then we will not span $\mathbb{R}^{2 \times 1}$. A generating set which is just big enough is called a basis. We can remove vectors which are linearly dependent on the remaining vectors without changing the span. Therefore, we should expect that a minimal spanning set is linearly independent.

Definition 5.5.1.

A **basis** for a vector space V is a set of vectors S such that

1. $V = \text{span}(S)$,
2. S is linearly independent.

Example 5.5.2. It is not hard to show that $B_1 = \{e_1, e_2\}$ and $B_2 = \{e_1, e_1 + e_2\}$ and $B_3 = \{e_2, e_1 + e_2\}$ are linearly independent sets. Furthermore, each spans $\mathbb{R}^{2 \times 1}$. Therefore, B_1, B_2, B_3 are bases for $\mathbb{R}^{2 \times 1}$. In particular, $B_1 = \{e_1, e_2\}$ is called the standard basis.

Example 5.5.3. I called $\{e_1, e_2, \dots, e_n\}$ the standard basis of $\mathbb{R}^{n \times 1}$. Since $v \in \mathbb{R}^n$ can be written as

$$v = \sum_i v_i e_i$$

it follows $\mathbb{R}^n = \text{span}\{e_i \mid 1 \leq i \leq n\}$. Moreover, linear independence of $\{e_i \mid 1 \leq i \leq n\}$ follows from a simple calculation:

$$0 = \sum_i c_i e_i \Rightarrow 0 = \left[\sum_i c_i e_i \right]_k = \sum_i c_i \delta_{ik} = c_k$$

hence $c_k = 0$ for all k . Thus $\{e_i \mid 1 \leq i \leq n\}$ is a basis for \mathbb{R}^n , we continue to call it the **standard basis** of \mathbb{R}^n . The vectors e_i are also called "unit-vectors".

Example 5.5.4. Since $A \in \mathbb{R}^{m \times n}$ can be written as

$$A = \sum_{i,j} A_{ij} E_{ij}$$

it follows $\mathbb{R}^{m \times n} = \text{span}\{E_{ij} \mid 1 \leq i \leq m, 1 \leq j \leq n\}$. Moreover, linear independence of $\{E_{ij} \mid 1 \leq i \leq m, 1 \leq j \leq n\}$ follows from a simple calculation:

$$0 = \sum_{i,j} c_{ij} E_{ij} \Rightarrow 0 = \left[\sum_{i,j} c_{ij} E_{ij} \right]_{kl} = \sum_{i,j} c_{ij} \delta_{ik} \delta_{jl} = c_{kl}$$

hence $c_{kl} = 0$ for all k, l . Thus $\{E_{ij} \mid 1 \leq i \leq m, 1 \leq j \leq n\}$ is a basis for $\mathbb{R}^{m \times n}$, we continue to call it the **standard basis** of $\mathbb{R}^{m \times n}$. The matrices E_{ij} are also called "unit-matrices".

Definition 5.5.5.

Suppose $B = \{f_1, f_2, \dots, f_n\}$ is a basis for V . If $v \in V$ has

$$v = v_1 f_1 + v_2 f_2 + \dots + v_n f_n$$

then $[v]_B = [v_1 \ v_2 \ \dots \ v_n]^T \in \mathbb{R}^n$ is called the **coordinate vector** of v with respect to B .

Technically, the each basis considered in the course is an "ordered basis". This means the set of vectors that forms the basis has an ordering to it. This is more structure than just a plain set since basic set theory does not distinguish $\{1, 2\}$ from $\{2, 1\}$. I should always say "we have an ordered basis" but I will not (and most people do not) say that in this course. Let it be understood that when we list the vectors in a basis they are listed in order and we cannot change that order without changing the basis. For example $v = [1, 2, 3]^T$ has coordinate vector $[v]_{B_1} = [1, 2, 3]^T$ with respect to $B_1 = \{e_1, e_2, e_3\}$. On the other hand, if $B_2 = \{e_2, e_1, e_3\}$ then the coordinate vector of v with respect to B_2 is $[v]_{B_2} = [2, 1, 3]^T$.

Proposition 5.5.6.

Suppose $B = \{f_1, f_2, \dots, f_n\}$ is a basis for V . Let $v \in V$, if $[x_i]$ and $[y_i]$ are coordinate vectors of v then $[x_i] = [y_i]$. In other words, the coordinates of a vector with respect to a basis are unique.

Proof: Suppose $v = x_1 f_1 + x_2 f_2 + \dots + x_n f_n$ and $v = y_1 f_1 + y_2 f_2 + \dots + y_n f_n$ notice that

$$\begin{aligned} 0 = v - v &= (x_1 f_1 + x_2 f_2 + \dots + x_n f_n) - (y_1 f_1 + y_2 f_2 + \dots + y_n f_n) \\ &= (x_1 - y_1) f_1 + (x_2 - y_2) f_2 + \dots + (x_n - y_n) f_n \end{aligned}$$

then by linear independence of the basis vectors we find $x_i - y_i = 0$ for each i . Thus $x_i = y_i$ for all i . Notice that linear independence and spanning were both necessary for the idea of a coordinate to make sense. \square

Example 5.5.7. Let $v = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$ find the coordinates of v relative to B_1, B_2 and B_3 where $B_1 = \{e_1, e_2\}$ and $B_2 = \{e_1, e_1 + e_2\}$ and $B_3 = \{e_2, e_1 + e_2\}$. We'll begin with the standard basis, (I hope you could see this without writing it)

$$v = \begin{bmatrix} 1 \\ 3 \end{bmatrix} = 1 \begin{bmatrix} 1 \\ 0 \end{bmatrix} + 3 \begin{bmatrix} 0 \\ 1 \end{bmatrix} = 1e_1 + 3e_2$$

thus $[v]_{B_1} = [1 \ 3]^T$. Find coordinates relative to the other two bases is not quite as obvious. Begin with B_2 . We wish to find x, y such that

$$v = xe_1 + y(e_1 + e_2)$$

we can just use brute-force,

$$v = e_1 + 3e_2 = xe_1 + y(e_1 + e_2) = (x + y)e_1 + ye_2$$

using linear independence of the standard basis we find $1 = x + y$ and $y = 3$ thus $x = 1 - 3 = -2$ and we see $v = -2e_1 + 3(e_1 + e_2)$ so $[v]_{B_2} = [-2 \ 3]^T$. This is interesting, the same vector can have different coordinate vectors relative to distinct bases. Finally, let's find coordinates relative to B_3 . I'll try to be more clever this time: we wish to find x, y such that

$$v = xe_2 + y(e_1 + e_2) \Leftrightarrow \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

We can solve this via the augmented coefficient matrix

$$\text{rref} \left[\begin{array}{cc|c} 0 & 1 & 1 \\ 1 & 1 & 3 \end{array} \right] = \left[\begin{array}{cc|c} 1 & 0 & 2 \\ 0 & 1 & 1 \end{array} \right] \Leftrightarrow x = 2, y = 1.$$

Thus, $[v]_{B_3} = [2 \ 1]^T$. Notice this is precisely the rightmost column in the rref matrix. Perhaps my approach for B_3 is a little like squashing a fly with a dumptruck. However, once we get to an example with 4-component vectors you may find the matrix technique useful.

Example 5.5.8. Given that $B = \{b_1, b_2, b_3, b_4\} = \{e_1 + e_2, e_2 + e_3, e_3 + e_4, e_4\}$ is a basis for $\mathbb{R}^{4 \times 1}$ find coordinates for $v = [1, 2, 3, 4]^T \in \mathbb{R}^{4 \times 1}$. Given the discussion in the preceding example it is clear we can find coordinates $[x_1, x_2, x_3, x_4]^T$ such that $v = \sum_i x_i b_i$ by calculating $\text{rref}[b_1|b_2|b_3|b_4|v]$ the rightmost column will be $[v]_B$.

$$\text{rref} \left[\begin{array}{cccc|c} 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 & 2 \\ 0 & 1 & 1 & 0 & 3 \\ 0 & 0 & 1 & 1 & 4 \end{array} \right] = \left[\begin{array}{cccc|c} 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 2 \\ 0 & 0 & 0 & 1 & 2 \end{array} \right] \Rightarrow \boxed{[v]_B = \begin{bmatrix} 1 \\ 1 \\ 2 \\ 2 \end{bmatrix}}$$

This calculation should be familiar. We discussed it at length in the spanning section.

Remark 5.5.9.

Curvilinear coordinate systems from calculus III are in a certain sense more general than the idea of a coordinate system in linear algebra. If we focus our attention on a single point in space then a curvilinear coordinate system will produce three linearly independent vectors which are tangent to the coordinate curves. However, if we go to a different point then the curvilinear coordinate system will produce three different vectors in general. For example, in spherical coordinates the radial unit vector is $e_\rho = \langle \cos \theta \sin \phi, \sin \theta \sin \phi, \cos \phi \rangle$ and you can see that different choices for the angles θ, ϕ make e_ρ point in different directions. In contrast, in this course we work with vector spaces. Our coordinate systems have the same basis vectors over the whole space. Vector spaces are examples of flat manifolds since they allow a single global coordinate system. Vector spaces also allow for curvilinear coordinates (which are not coordinates in the sense of linear algebra). However the converse is not true; spaces with nonzero curvature do not allow for global coordinates. I digress, we may have occasion to discuss these matters more cogently in our Advanced Calculus course (Math 332) offered in the Spring (join us)

Definition 5.5.10.

If a vector space V has a basis which consists of a finite number of vectors then we say that V is **finite-dimensional** vector space. Otherwise V is said to be **infinite-dimensional**

Example 5.5.11. $\mathbb{R}^n, \mathbb{R}^{m \times n}, P_n$ are examples of finite-dimensional vector spaces. On the other hand, $\mathcal{F}(\mathbb{R}), C^0(\mathbb{R}), C^1(\mathbb{R}), C^\infty(\mathbb{R})$ are infinite-dimensional.

Example 5.5.12. We can prove that S from Example 5.3.18 is linearly independent, thus symmetric 2×2 matrices have a S as a basis

$$S = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \right\}$$

thus the dimension of the vector space of 2×2 symmetric matrices is 3. (notice \bar{S} from that example is not a basis because it is linearly dependent). While we're thinking about this let's find the coordinates of $A = \begin{bmatrix} 1 & 3 \\ 3 & 2 \end{bmatrix}$ with respect to S . Denote $[A]_S = [x, y, z]^T$. We calculate,

$$\begin{bmatrix} 1 & 3 \\ 3 & 2 \end{bmatrix} = x \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} + y \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} + z \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \Rightarrow [A]_S = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}.$$

5.5.1 how to calculate a basis for a span of row or column vectors

Given some subspace of \mathbb{R}^n we would like to know how to find a basis for that space. In particular, if $V = \text{span}\{v_1, v_2, \dots, v_k\}$ then what is a basis for W ? Likewise, given some set of row vectors $W = \{w_1, w_2, \dots, w_k\} \subset \mathbb{R}^{1 \times n}$ how can we select a basis for $\text{span}(W)$. We would like to find answers to these question since most subspaces are characterized either as spans or solution sets (see the next section on $\text{Null}(A)$). We already have the tools to answer these questions, we just need to apply them to the tasks at hand.

Proposition 5.5.13.

Let $W = \text{span}\{v_1, v_2, \dots, v_k\} \subset \mathbb{R}^n$ then a basis for W can be obtained by selecting the vectors that reside in the pivot columns of $[v_1|v_2|\dots|v_k]$.

Proof: this is immediately obvious from Proposition 5.4.8. \square

The proposition that follows is also follows immediately from Proposition 5.4.8.

Proposition 5.5.14.

Let $A \in \mathbb{R}^{m \times n}$ the pivot columns of A form a basis for $\text{Col}(A)$.

Example 5.5.15. Suppose A is given as below: (I omit the details of the Gaussian elimination)

$$A = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 2 & 1 & 4 & 1 \\ 0 & 0 & 0 & 3 \end{bmatrix} \quad \Rightarrow \quad \text{rref}[A] = \begin{bmatrix} 1 & 0 & 5/3 & 0 \\ 0 & 1 & 2/3 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

Identify that columns 1,2 and 4 are pivot columns. Moreover,

$$\text{Col}(A) = \text{span}\{\text{col}_1(A), \text{col}_2(A), \text{col}_4(A)\}$$

In particular we can also read how the second column is a linear combination of the basis vectors.

$$\begin{aligned} \text{col}_3(A) &= \frac{5}{3}\text{col}_1(A) + \frac{2}{3}\text{col}_2(A) \\ &= \frac{5}{3}[1, 2, 0]^T + \frac{2}{3}[2, 1, 0]^T \\ &= [5/3, 10/3, 0]^T + [4/3, 2/3, 0]^T \\ &= [3, 4, 0]^T \end{aligned}$$

What if we want a basis for $\text{Row}(A)$ which consists of rows in A itself?

Proposition 5.5.16.

Let $W = \text{span}\{w_1, w_2, \dots, w_k\} \subset \mathbb{R}^{1 \times n}$ and construct A by concatenating the row vectors in W into a matrix A :

$$A = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_k \end{bmatrix}$$

A basis for W is given by the transposes of the pivot columns for A^T .

Proof: this is immediately obvious from Proposition 5.4.12. \square

The proposition that follows is also follows immediately from Proposition 5.4.12.

Proposition 5.5.17.

Let $A \in \mathbb{R}^{m \times n}$ the rows which are transposes of the pivot columns of A^T form a basis for $\text{Row}(A)$.

Example 5.5.18.

$$A^T = \begin{bmatrix} 1 & 2 & 0 \\ 2 & 1 & 0 \\ 3 & 4 & 0 \\ 4 & 1 & 3 \end{bmatrix} \Rightarrow \text{rref}[A^T] = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}.$$

Notice that each column is a pivot column in A^T thus a basis for $\text{Row}(A)$ is simply the set of all rows of A ; $\text{Row}(A) = \text{span}\{[1, 2, 3, 4], [2, 1, 4, 1], [0, 0, 1, 0]\}$ and the spanning set is linearly independent.

Example 5.5.19.

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 2 & 2 & 2 \\ 3 & 4 & 0 \\ 5 & 6 & 2 \end{bmatrix} \Rightarrow A^T = \begin{bmatrix} 1 & 2 & 3 & 5 \\ 1 & 2 & 4 & 6 \\ 1 & 2 & 0 & 2 \end{bmatrix} \Rightarrow \text{rref}[A^T] = \begin{bmatrix} 1 & 2 & 0 & 2 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

We deduce that rows 1 and 3 of A form a basis for $\text{Row}(A)$. Notice that $\text{row}_2(A) = 2\text{row}_1(A)$ and $\text{row}_4(A) = \text{row}_3(A) + 2\text{row}_1(A)$. We can read linear dependencies of the rows from the corresponding linear dependencies of the columns in the rref of the transpose.

The preceding examples are nice, but what should we do if we want to find both a basis for $\text{Col}(A)$ and $\text{Row}(A)$ for some given matrix? Let's pause to think about how elementary row operations modify the row and column space of a matrix. In particular, let A be a matrix and let A' be the result of performing an elementary row operation on A . It is fairly obvious that

$$\text{Row}(A) = \text{Row}(A').$$

Think about it. If we swap two rows that just switches the order of the vectors in the span that makes $\text{Row}(A)$. On the other hand if we replace one row with a nontrivial linear combination of itself and other rows then that will not change the span either. Column space is not so easy though. Notice that elementary row operations can change the column space. For example,

$$A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \Rightarrow \text{rref}[A] = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}$$

has $\text{Col}(A) = \text{span}\{[1, 1]^T\}$ whereas $\text{Col}(\text{rref}(A)) = \text{span}\{[1, 0]^T\}$. We cannot hope to use columns of $\text{ref}(A)$ (or $\text{rref}(A)$) for a basis of $\text{Col}(A)$. That's no big problem though because we already have the CCP-principle which helped us pick out a basis for $\text{Col}(A)$. Let's collect our thoughts:

Proposition 5.5.20.

Let $A \in \mathbb{R}^{m \times n}$ then a basis for $Col(A)$ is given by the pivot columns in A and a basis for $Row(A)$ is given by the nonzero rows in $ref(A)$.

This means we can find a basis for $Col(A)$ and $Row(A)$ by performing the forward pass on A . We need only calculate the $ref(A)$ as the pivot columns are manifest at the end of the forward pass.

Example 5.5.21.

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 2 & 3 \end{bmatrix} \xrightarrow[\underline{r_3 - r_1 \rightarrow r_3}]{r_2 - r_1 \rightarrow r_2} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 1 & 2 \end{bmatrix} \xrightarrow{r_1 \leftrightarrow r_2} \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 2 \\ 0 & 0 & 0 \end{bmatrix} = ref[A]$$

We deduce that $\{[1, 1, 1], [0, 1, 2]\}$ is a basis for $Row(A)$ whereas $\{[1, 1, 1]^T, [1, 1, 2]^T\}$ is a basis for $Col(A)$. Notice that if I wanted to reveal further linear dependencies of the non-pivot columns on the pivot columns of A it would be wise to calculate $rref[A]$ by making the backwards pass on $ref[A]$.

$$\begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 2 \\ 0 & 0 & 0 \end{bmatrix} \xrightarrow{r_1 - r_2 \rightarrow r_1} \begin{bmatrix} 1 & 0 & -1 \\ 0 & 1 & 2 \\ 0 & 0 & 0 \end{bmatrix} = rref[A]$$

From which I can read $col_3(A) = 2col_2(A) - col_1(A)$, a fact which is easy to verify.

Example 5.5.22.

$$A = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 1 & 3 & 8 & 10 \\ 1 & 2 & 4 & 11 \end{bmatrix} \xrightarrow[\underline{r_3 - r_1 \rightarrow r_3}]{r_2 - r_1 \rightarrow r_2} \begin{bmatrix} 1 & 2 & 3 & 4 \\ 0 & 1 & 5 & 6 \\ 0 & 0 & 1 & 7 \end{bmatrix} = ref[A]$$

We find that $Row(A)$ has basis

$$\{[1, 2, 3, 4], [0, 1, 5, 6], [0, 0, 1, 7]\}$$

and $Col(A)$ has basis

$$\left\{ \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ 3 \\ 2 \end{bmatrix}, \begin{bmatrix} 3 \\ 8 \\ 4 \end{bmatrix} \right\}$$

Proposition 5.5.20 was the guide for both examples above.

5.5.2 calculating basis of a solution set

Often a subspace is described as the solution set of some equation $Ax = 0$. How do we find a basis for $Null(A)$? If we can do that we find a basis for subspaces which are described by some equation.

Proposition 5.5.23.

Let $A \in \mathbb{R}^{m \times n}$ and define $W = Null(A)$. A basis for W is obtained from the solution set of $Ax = 0$ by writing the solution as a linear combination where the free variables appear as coefficients in the vector-sum.

Proof: $x \in W$ implies $Ax = 0$. Denote $x = [x_1, x_2, \dots, x_n]^T$. Suppose that $rref[A]$ has r -pivot columns (we must have $0 \leq r \leq n$). There will be $(m - r)$ -rows which are zero in $rref(A)$ and $(n - r)$ -columns which are not pivot columns. The non-pivot columns correspond to free-variables in the solution. Define $p = n - r$ for convenience. Suppose that $x_{i_1}, x_{i_2}, \dots, x_{i_p}$ are free whereas $x_{j_1}, x_{j_2}, \dots, x_{j_r}$ are functions of the free variables: in particular they are linear combinations of the free variables as prescribed by $rref[A]$. There exist constants b_{ij} such that

$$\begin{aligned} x_{j_1} &= b_{11}x_{i_1} + b_{12}x_{i_2} + \dots + b_{1p}x_{i_p} \\ x_{j_2} &= b_{21}x_{i_1} + b_{22}x_{i_2} + \dots + b_{2p}x_{i_p} \\ &\vdots \quad \quad \quad \vdots \quad \quad \quad \dots \quad \quad \quad \vdots \\ x_{j_r} &= b_{r1}x_{i_1} + b_{r2}x_{i_2} + \dots + b_{rp}x_{i_p} \end{aligned}$$

For convenience of notation assume that the free variables are put at the end of the list. We have

$$\begin{aligned} x_1 &= b_{11}x_{r+1} + b_{12}x_{r+2} + \dots + b_{1p}x_n \\ x_2 &= b_{21}x_{r+1} + b_{22}x_{r+2} + \dots + b_{2p}x_n \\ &\vdots \quad \quad \quad \vdots \quad \quad \quad \dots \quad \quad \quad \vdots \\ x_r &= b_{r1}x_{r+1} + b_{r2}x_{r+p+2} + \dots + b_{rp}x_n \end{aligned}$$

and $x_j = x_j$ for $j = r + 1, r + 2, \dots, r + p = n$ (those are free, we have no conditions on them, they can take any value). We find,

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_r \\ x_{r+1} \\ x_{r+2} \\ \vdots \\ x_n \end{bmatrix} = x_{r+1} \begin{bmatrix} b_{11} \\ b_{21} \\ \vdots \\ b_{r1} \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} + x_{r+2} \begin{bmatrix} b_{12} \\ b_{22} \\ \vdots \\ b_{r2} \\ 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix} + \dots + x_n \begin{bmatrix} b_{1p} \\ b_{2p} \\ \vdots \\ b_{rp} \\ 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}$$

We define the vectors in the sum above as v_1, v_2, \dots, v_p . If any of the vectors, say v_j , was linearly dependent on the others then we would find that the variable x_{r+j} was likewise dependent on the

other free variables. This would contradict the fact that the variable x_{r+j} was free. Consequently the vectors v_1, v_2, \dots, v_p are linearly independent. Moreover, they span the null-space by virtue of their construction. \square

Didn't follow the proof above? No problem. See the examples to follow here. These are just the proof in action for specific cases. We've done these sort of calculations in §1.3. We're just adding a little more insight here.

Example 5.5.24. Find a basis for the null space of A given below,

$$A = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 2 & 2 & 0 & 0 & 1 \\ 4 & 4 & 4 & 0 & 0 \end{bmatrix}$$

Gaussian elimination on the augmented coefficient matrix reveals (see Example 1.2.7 for details of the Gaussian elimination)

$$\text{rref} \begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 2 & 2 & 0 & 0 & 1 \\ 4 & 4 & 4 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & -1 & 1/2 \\ 0 & 0 & 1 & 0 & -1/2 \end{bmatrix}$$

Denote $x = [x_1, x_2, x_3, x_4, x_5]^T$ in the equation $Ax = 0$ and identify from the calculation above that x_4 and x_5 are free thus solutions are of the form

$$\begin{aligned} x_1 &= -x_4 \\ x_2 &= x_4 - \frac{1}{2}x_5 \\ x_3 &= \frac{1}{2}x_5 \\ x_4 &= x_4 \\ x_5 &= x_5 \end{aligned}$$

for all $x_4, x_5 \in \mathbb{R}$. We can write these results in vector form to reveal the basis for $\text{Null}(A)$,

$$x = \begin{bmatrix} -x_4 \\ x_4 - \frac{1}{2}x_5 \\ \frac{1}{2}x_5 \\ x_4 \\ x_5 \end{bmatrix} = x_4 \begin{bmatrix} -1 \\ 1 \\ 0 \\ 1 \\ 0 \end{bmatrix} + x_5 \begin{bmatrix} 0 \\ -\frac{1}{2} \\ \frac{1}{2} \\ 0 \\ 1 \end{bmatrix}$$

It follows that the basis for $\text{Null}(A)$ is simply

$$\left\{ \begin{bmatrix} -1 \\ 1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ -\frac{1}{2} \\ \frac{1}{2} \\ 0 \\ 1 \end{bmatrix} \right\}$$

Of course, you could multiply the second vector by 2 if you wish to avoid fractions. In fact there is a great deal of freedom in choosing a basis. We simply show one way to do it.

Example 5.5.25. Find a basis for the null space of A given below,

$$A = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

Gaussian elimination on the augmented coefficient matrix reveals:

$$\text{rref} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Denote $x = [x_1, x_2, x_3, x_4]^T$ in the equation $Ax = 0$ and identify from the calculation above that x_2 , x_3 and x_4 are free thus solutions are of the form

$$\begin{aligned} x_1 &= -x_2 - x_3 - x_4 \\ x_2 &= x_2 \\ x_3 &= x_3 \\ x_4 &= x_4 \end{aligned}$$

for all $x_2, x_3, x_4 \in \mathbb{R}$. We can write these results in vector form to reveal the basis for $\text{Null}(A)$,

$$x = \begin{bmatrix} -x_2 - x_3 - x_4 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = x_2 \begin{bmatrix} -1 \\ 1 \\ 0 \\ 0 \end{bmatrix} + x_3 \begin{bmatrix} -1 \\ 0 \\ 1 \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

It follows that the basis for $\text{Null}(A)$ is simply

$$\left\{ \begin{bmatrix} -1 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \end{bmatrix} \right\}$$

5.5.3 what is dimension?

We prove a number of theorems in the section which show that dimension is a well-defined quantity for a finite dimensional vector space. Up to this point we have only used the phrase "finite-dimensional" to mean that there exists one basis with finitely many vectors. In this section we prove that if that is the case then all other bases for the vector space must likewise have the same number of basis vectors. In addition we give several existence theorems which are of great theoretical importance. Finally, we discuss dimensions of column, row and null space of a matrix.

The proposition that follows is the baby version of Proposition 5.5.30. I include this proposition in the notes because the proof is fun.

Proposition 5.5.26.

Let V be a finite-dimensional vector space and suppose $B = \{b_1, b_2, \dots, b_n\}$ is any basis of V ,

1. $B \cup \{v\}$ is linearly dependent
2. for any $1 \leq k \leq n$, $B - \{b_k\}$ does not span V

Proof of (1.): Since B spans V it follows that v is a linear combination of vectors in B thus $B \cup \{v\}$ is linearly dependent.

Proof of (2.): We argue that $b_k \notin \text{span}(B - \{b_k\})$. Argue by contradiction. Suppose that $b_k \in \text{span}(B - \{b_k\})$ then there exist constants $c_1, c_2, \dots, \widehat{c_k}, c_n$ such that

$$b_k = c_1 b_1 + c_2 b_2 + \dots + \widehat{c_k b_k} + \dots + c_n b_n$$

but this contradicts the linear independence of the basis as

$$c_1 b_1 + c_2 b_2 + \dots - b_k + \dots + c_n b_n = 0$$

does not imply all the coefficients are zero. Therefore, using proof by contradiction, $\text{span}(B - \{b_k\}) \neq V$. \square

Proposition 5.5.27.

Let V be a finite-dimensional vector space and suppose $B = \{b_1, b_2, \dots, b_n\}$ is any basis of V then any other basis for V also has n -elements.

Proof: Suppose $B = \{b_1, b_2, \dots, b_n\}$ and $F = \{f_1, f_2, \dots, f_p\}$ are both bases for a vector space V . Since F is a basis it follows $b_k \in \text{span}(F)$ for all k so there exist constants c_{ik} such that

$$b_k = c_{1k} f_1 + c_{2k} f_2 + \dots + c_{pk} f_p$$

for $k = 1, 2, \dots, n$. Likewise, since $f_j \in \text{span}(B)$ there exist constants d_{ij} such that

$$f_j = d_{1j} b_1 + d_{2j} b_2 + \dots + d_{nj} b_n$$

for $j = 1, 2, \dots, p$. Substituting we find

$$\begin{aligned} f_j &= d_{1j} b_1 + d_{2j} b_2 + \dots + d_{nj} b_n \\ &= d_{1j} (c_{11} f_1 + c_{21} f_2 + \dots + c_{p1} f_p) + \\ &\quad + d_{2j} (c_{12} f_1 + c_{22} f_2 + \dots + c_{p2} f_p) + \\ &\quad + \dots + d_{nj} (c_{1n} f_1 + c_{2n} f_2 + \dots + c_{pn} f_p) \\ &= (d_{1j} c_{11} + d_{2j} c_{12} + \dots + d_{nj} c_{1n}) f_1 \\ &\quad + (d_{1j} c_{21} + d_{2j} c_{22} + \dots + d_{nj} c_{2n}) f_2 + \\ &\quad + \dots + (d_{1j} c_{p1} + d_{2j} c_{p2} + \dots + d_{nj} c_{pn}) f_p \end{aligned}$$

Suppose $j = 1$. We deduce, by the linear independence of F , that

$$d_{11}c_{11} + d_{21}c_{12} + \cdots d_{n1}c_{1n} = 1$$

from comparing coefficients of f_1 , whereas for f_2 we find,

$$d_{11}c_{21} + d_{21}c_{22} + \cdots d_{n1}c_{2n} = 0$$

likewise, for f_q with $q \neq 1$,

$$d_{11}c_{q1} + d_{21}c_{q2} + \cdots d_{n1}c_{qn} = 0$$

Notice we can rewrite all of these as

$$\delta_{q1} = c_{q1}d_{11} + c_{q2}d_{21} + \cdots c_{qn}d_{n1}$$

Similarly, for arbitrary j we'll find

$$\delta_{qj} = c_{q1}d_{1j} + c_{q2}d_{2j} + \cdots c_{qn}d_{nj}$$

If we define $C = [c_{ij}] \in \mathbb{R}^{p \times n}$ and $D = [d_{ij}] \in \mathbb{R}^{n \times p}$ then we can translate the equation above into the matrix equation that follows:

$$CD = I_p.$$

We can just as well argue that

$$DC = I_n$$

From your Problem Set, we learned that $tr(AB) = tr(BA)$ if the product AB and BA are both defined. Moreover, you also proved $tr(I_p) = p$ and $tr(I_q) = q$. It follows that,

$$tr(CD) = tr(DC) \Rightarrow tr(I_p) = tr(I_q) \Rightarrow p = q.$$

Since the bases were arbitrary this proves any pair have the same number of vectors. \square

Given the preceding proposition the following definition is logical.

Definition 5.5.28.

If V is a finite-dimensional vector space then the **dimension** of V is the number of vectors in any basis of V and it is denoted $dim(V)$.

Example 5.5.29. Let me state the dimensions which follow from the standard bases of \mathbb{R}^n and $\mathbb{R}^{m \times n}$ respective,

$$dim(\mathbb{R}^n) = n \quad dim(\mathbb{R}^{m \times n}) = mn$$

these results follow from counting.

Proposition 5.5.30.

Suppose V is a vector space with $\dim(V) = n$.

1. If S is a set with more than n vectors then S is linearly dependent.
2. If S is a set with less than n vectors then S does not generate V .

Proof of (1.): Suppose $S = \{s_1, s_2, \dots, s_m\}$ has m vectors and $m > n$. Let $B = \{b_1, b_2, \dots, b_n\}$ be a basis of V . Consider the corresponding set of coordinate vectors of the vectors in S , we denote

$$[S]_B = \{[s_1]_B, [s_2]_B, \dots, [s_m]_B\}.$$

The set $[S]_B$ has m vectors in \mathbb{R}^n and $m > n$ therefore by Proposition 2.5.9 we know $[S]_B$ is a linearly dependent set. Therefore at least one, say $[s_j]_B$, vector can be written as a linear combination of the other vectors in $[S]_B$ thus there exist constants c_i with (this is a vector equation)

$$[s_j]_B = c_1[s_1]_B + c_2[s_2]_B + \dots + \widehat{c_j[s_j]_B} + \dots + c_m[s_m]_B$$

Also notice that (introducing a new shorthand $B[s_j]$ which is not technically matrix multiplication since b_i are not column vectors generally, they could be chickens for all we know)

$$s_j = B[s_j] = s_{j1}b_1 + s_{j2}b_2 + \dots + s_{jn}b_n$$

We also know, using the notation $([s_j]_B)_k = s_{jk}$,

$$s_{jk} = c_1s_{1k} + c_2s_{2k} + \dots + \widehat{c_js_{jk}} + \dots + c_ms_{mk}$$

for $k = 1, 2, \dots, n$. Plug these into our s_j equation,

$$\begin{aligned} s_j &= (c_1s_{11} + c_2s_{21} + \dots + \widehat{c_js_{j1}} + \dots + c_ms_{m1})b_1 + \\ &\quad (c_1s_{12} + c_2s_{22} + \dots + \widehat{c_js_{j2}} + \dots + c_ms_{m2})b_2 + \\ &\quad + \dots + (c_1s_{1n} + c_2s_{2n} + \dots + \widehat{c_js_{jn}} + \dots + c_ms_{mn})b_n \\ &= c_1(s_{11}b_1 + s_{12}b_2 + \dots + s_{1n}b_n) + \\ &\quad c_2(s_{21}b_1 + s_{22}b_2 + \dots + s_{2n}b_n) + \\ &\quad + \dots + c_m(s_{m1}b_1 + s_{m2}b_2 + \dots + s_{mn}b_n) : \text{ excluding } c_j(\dots) \\ &= c_1s_1 + c_2s_2 + \dots + \widehat{c_js_j} + \dots + c_ns_n. \end{aligned}$$

Well this is a very nice result, the same linear combination transfers over to the abstract vectors. Clearly s_j linearly depends on the other vectors in S so S is linearly dependent. The heart of the proof was Proposition 2.5.9 and the rest was just battling notation.

Proof of (2.): Use the corresponding result for \mathbb{R}^n which was given by Proposition 2.5.8. Given m abstract vectors if we concatenate their coordinate vectors we will find a matrix $[S]$ in $\mathbb{R}^{n \times m}$

with $m < n$ and as such there will be some choice of the vector b for which $[S]x \neq b$. The abstract vector corresponding to b will not be covered by the span of S . \square

Anton calls the following proposition the "Plus/Minus" Theorem.

Proposition 5.5.31.

Let V be a vector space and suppose S is a nonempty set of vectors in V .

1. If S is linearly independent a nonzero vector $v \notin \text{span}(S)$ then $S \cup \{v\}$ is a linearly independent set.
2. If $v \in S$ is a linear combination of other vectors in S then $\text{span}(S - \{v\}) = \text{span}(S)$.

Proof of (1.): Suppose $S = \{s_1, s_2, \dots, s_k\}$ and consider,

$$c_1 s_1 + c_2 s_2 + \dots + c_k s_k + c_{k+1} v = 0$$

If $c_{k+1} \neq 0$ it follows that v is a linear combination of vectors in S but this is impossible so $c_{k+1} = 0$. Then since S is linear independent

$$c_1 s_1 + c_2 s_2 + \dots + c_k s_k = 0 \Rightarrow c_1 = c_2 = \dots = c_k = 0$$

thus $S \cup \{v\}$ is linearly independent.

Proof of (2.): Suppose $v = s_j$. We are given that there exist constants d_i such that

$$s_j = d_1 s_1 + \dots + \widehat{d_j s_j} + \dots + d_k s_k$$

Let $w \in \text{span}(S)$ so there exist constants c_i such that

$$w = c_1 s_1 + c_2 s_2 + \dots + c_j s_j + \dots + c_k s_k$$

Now we can substitute the linear combination with d_i -coefficients for s_j ,

$$\begin{aligned} w &= c_1 s_1 + c_2 s_2 + \dots + c_j (d_1 s_1 + \dots + \widehat{d_j s_j} + \dots + d_k s_k) + \dots + c_k s_k \\ &= (c_1 + c_j d_1) s_1 + (c_2 + c_j d_2) s_2 + \dots + \widehat{c_j d_j s_j} + \dots + (c_k + c_j d_k) s_k \end{aligned}$$

thus w is a linear combination of vectors in S , but not $v = s_j$, thus $w \in \text{span}(S - \{v\})$ and we find $\text{span}(S) \subseteq \text{span}(S - \{v\})$.

Next, suppose $y \in \text{span}(S - \{v\})$ then y is a linear combination of vectors in $S - \{v\}$ hence y is a linear combination of vectors in S and we find $y \in \text{span}(S)$ so $\text{span}(S - \{v\}) \subseteq \text{span}(S)$. (this inclusion is generally true even if v is linearly independent from other vectors in S). We conclude that $\text{span}(S) = \text{span}(S - \{v\})$. \square

Proposition 5.5.32.

Let V be an n -dimensional vector space. A set S with n -vectors is a basis for V if S is either linearly independent or if $\text{span}(S) = V$.

Proof: Assume S has n -vectors which are linearly independent in a vector space V with dimension n . Suppose towards a contradiction that S does not span V . Then there exists $v \in V$ such that $v \notin \text{span}(S)$. Then by Proposition 5.5.31 we find $V \cup \{v\}$ is linearly independent. But, Proposition 5.5.30 the set $V \cup \{v\}$ is linearly dependent. This is a contradiction, thus S spans V and we find S is a basis.

Assume S has n -vectors which span a vector space V with dimension n . Suppose towards a contradiction that S is not linearly independent. This means there exists $v \in S$ which is a linear combination of other vectors in S . Therefore, by 5.5.30, S does not span V . This contradicts the assumption $\text{span}(S) = V$ therefore S is linearly independent and consequently S is a basis. \square

Remark 5.5.33.

Intuitively speaking, linear independence is like injectivity for functions whereas spanning is like the onto property for functions. Suppose A is a finite set. If a function $f : A \rightarrow A$ is 1-1 then it is onto. Also if the function is onto then it is 1-1. The finiteness of A is what blurs the concepts. For a vector space, we also have a sort of finiteness in play if $\dim(V) = n$. When a set with $\dim(V)$ -vectors spans (like onto) V then it is automatically linearly independent. When a set with $\dim(V)$ -vectors is linearly independent (like 1-1) V then it automatically spans V . However, in an infinite dimensional vector space this need not be the case. For example, d/dx is a surjective linear mapping on $\mathbb{R}[x] = \text{span}\{1, x, x^2, x^3, \dots\}$ however if $f, g \in \mathbb{R}[x]$ and $df/dx = dg/dx$ we can only conclude that $f = g + c$ thus d/dx is not injective on vector space of polynomials in x . Many theorems we discuss do hold in the infinite dimensional context, but you have to be careful.

Proposition 5.5.34.

Let S be a subset of a finite dimensional vector space V .

1. If $\text{span}(S) = V$ but S is not a basis then S can be modified to make a basis by removing redundant vectors.
2. If S is linearly independent and $\text{span}(S) \neq V$ then S can be modified to make a basis by unioning vectors outside $\text{span}(S)$.

Proof of (1.): If $\text{span}(S) = V$ but S is not a basis we find S is linearly dependent. (if S is linearly independent then Proposition 5.5.32 says S is a basis which is a contradiction). Since S is linearly dependent we can write some $v \in S$ as a linear combination of other vectors in S . Furthermore, by Proposition 5.5.30 $\text{span}(S) = \text{span}(S - \{v\})$. If $S - \{v\}$ is linearly independent then $S - \{v\}$ is a

basis. Otherwise $S - \{v\}$ is linearly dependent and we can remove another vector. Continue until the resulting set is linearly independent (we know this happens when there are just $\dim(V)$ -vectors in the set so this is not an endless loop)

Proof of (2.): If S is linearly independent but $\text{span}(S) \neq V$ then there exists $v \in V$ but $v \notin \text{span}(S)$. Proposition 5.5.31 shows that $S \cup \{v\}$ is linearly independent. If $\text{span}(S \cup \{v\}) = V$ then $S \cup \{v\}$ is a basis. Otherwise there is still some vector outside $\text{span}(S \cup \{v\}) = V$ and we can repeat the argument for that vector and so forth until we generate a set which spans V . Again we know this is not an endless loop because V is finite dimensional and once the set is linearly independent and contains $\dim(V)$ vectors it must be a basis (see Proposition 5.5.32). \square

Remark 5.5.35.

We already saw in the previous sections that we can implement part (1.) of the preceding proposition in \mathbb{R}^n and $\mathbb{R}^{1 \times n}$ through matrix calculations. There are really nice results about row and column spaces which show us precisely which vectors we need to remove or add to obtain a basis. I'll probably ask a homework question which tackles the question in the abstract. Once you understand the \mathbb{R}^n -case you can do the abstract case by lifting the arguments through the coordinate maps. We've already seen this "lifting" idea come into play in several proof of Proposition 5.5.30. Part (2.) involves making a choice. How do you choose a vector outside the span? I leave this question to the reader for the moment.

Proposition 5.5.36.

If V is a finite-dimensional vector space and $W \leq V$ then $\dim(W) \leq \dim(V)$. Moreover, if $\dim(V) = \dim(W)$ then $V = W$.

Proof: Left to the reader, I don't want to be too greedy. Besides, I need something to put on the test⁵. \square

These were defined before, I restate them here along with their dimensions for convenience.

Definition 5.5.37.

Let $A \in \mathbb{R}^{m \times n}$. We define

1. $\text{Col}(A) = \text{span}\{\text{col}_j(A) | j = 1, 2, \dots, n\}$ and $r = \text{rank}(A) = \dim(\text{Col}(A))$
2. $\text{Row}(A) = \text{span}\{\text{row}_i(A) | i = 1, 2, \dots, m\}$
3. $\text{Null}(A) = \{x \in \mathbb{R}^n | Ax = 0\}$ and $\nu = \text{nullity}(A) = \dim(\text{Null}(A))$

⁵I'm kidding

Proposition 5.5.38.

Let $A \in \mathbb{R}^{m \times n}$ then $\dim(\text{Row}(A)) = \dim(\text{Col}(A))$

Proof: By Proposition 5.5.14 we know the number of vectors in the basis for $\text{Col}(A)$ is the number of pivot columns in A . Likewise, Proposition 5.5.20 showed the number of vectors in the basis for $\text{Row}(A)$ was the number of nonzero rows in $\text{ref}(A)$. But the number of pivot columns is precisely the number of nonzero rows in $\text{ref}(A)$ therefore, $\dim(\text{Row}(A)) = \dim(\text{Col}(A))$. \square

Proposition 5.5.39.

Let $A \in \mathbb{R}^{m \times n}$ then $n = \text{rank}(A) + \text{nullity}(A)$.

Proof: The proof of Proposition 5.5.23 makes is clear that if a $m \times n$ matrix A has r -pivot columns then there will be $n - r$ vectors in the basis of $\text{Null}(A)$. It follows that

$$\text{rank}(A) + \text{nullity}(A) = r + (n - r) = n.$$

5.6 general theory of linear systems

Let $A \in \mathbb{R}^{m \times n}$ we should notice that $\text{Null}(A) \leq \mathbb{R}^n$ is only possible since homogeneous systems of the form $Ax = 0$ have the nice property that linear combinations of solutions is again a solution:

Proposition 5.6.1.

Let $Ax = 0$ denote a homogeneous linear system of m -equations and n -unknowns. If v_1 and v_2 are solutions then any linear combination $c_1v_1 + c_2v_2$ is also a solution of $Ax = 0$.

Proof: Suppose $Av_1 = 0$ and $Av_2 = 0$. Let $c_1, c_2 \in \mathbb{R}$ and recall Theorem 3.3.16 part 13,

$$A(c_1v_1 + c_2v_2) = c_1Av_1 + c_2Av_2 = c_10 + c_20 = 0.$$

Therefore, $c_1v_1 + c_2v_2 \in \text{Sol}_{[A|0]}$. \square

We proved this before, but I thought it might help to see it again here.

Proposition 5.6.2.

Let $A \in \mathbb{R}^{m \times n}$. If v_1, v_2, \dots, v_k are solutions of $Av = 0$ then $V = [v_1|v_2|\dots|v_k]$ is a **solution matrix** of $Av = 0$ (V a solution matrix of $Av = 0$ iff $AV = 0$)

Proof: Let $A \in \mathbb{R}^{m \times n}$ and suppose $Av_i = 0$ for $i = 1, 2, \dots, k$. Let $V = [v_1|v_2|\dots|v_k]$ and use the solution concatenation Proposition 3.6.1,

$$AV = A[v_1|v_2|\dots|v_k] = [Av_1|Av_2|\dots|Av_k] = [0|0|\dots|0] = 0.$$

. \square .

In simple terms, a solution matrix of a linear system is a matrix in which each column is itself a solution to the system.

Proposition 5.6.3.

Let $A \in \mathbb{R}^{m \times n}$. The system of equations $Ax = b$ is consistent iff $b \in \text{Col}(A)$.

Proof: Observe,

$$\begin{aligned} Ax = b &\Leftrightarrow \sum_{i,j} A_{ij}x_j e_i = b \\ &\Leftrightarrow \sum_j x_j \sum_i A_{ij} e_i = b \\ &\Leftrightarrow \sum_j x_j \text{col}_j(A) = b \\ &\Leftrightarrow b \in \text{Col}(A) \end{aligned}$$

Therefore, the existence of a solution to $Ax = b$ is interchangeable with the statement $b \in \text{Col}(A)$. They both amount to saying that b is a linear combination of columns of A . \square

Proposition 5.6.4.

Let $A \in \mathbb{R}^{m \times n}$ and suppose the system of equations $Ax = b$ is consistent. We find $x \in \mathbb{R}^n$ is a solution of the system if and only if it can be written in the form

$$x = x_h + x_p = c_1 v_1 + c_2 v_2 + \cdots + c_\nu v_\nu + x_p$$

where $Ax_h = 0$, $\{v_j\}_{j=1}^\nu$ are a basis for $\text{Null}(A)$, and $Ax_p = b$. We call x_h the homogeneous solution and x_p is the nonhomogeneous solution.

Proof: Suppose $Ax = b$ is consistent then $b \in \text{Col}(A)$ therefore there exists $x_p \in \mathbb{R}^n$ such that $Ax_p = b$. Let x be any solution. We have $Ax = b$ thus observe

$$A(x - x_p) = Ax - Ax_p = Ax - b = 0 \Rightarrow (x - x_p) \in \text{Null}(A).$$

Define $x_h = x - x_p$ it follows that there exist constants c_i such that $x_h = c_1 v_1 + c_2 v_2 + \cdots + c_\nu v_\nu$ since the vectors v_i span the null space.

Conversely, suppose $x = x_p + x_h$ where $x_h = c_1 v_1 + c_2 v_2 + \cdots + c_\nu v_\nu \in \text{Null}(A)$ then it is clear that

$$Ax = A(x_p + x_h) = Ax_p + Ax_h = b + 0 = b$$

thus $x = x_p + x_h$ is a solution. \square

Example 5.6.5. Consider the system of equations $x + y + z = 1, x + z = 1$. In matrix notation,

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \Rightarrow \text{rref}[A|b] = \text{rref} \left[\begin{array}{ccc|c} 1 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right]$$

It follows that $x = 1 - y - z$ is a solution for any choice of $y, z \in \mathbb{R}$.

$$v = \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 - y - z \\ y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} + y \begin{bmatrix} -1 \\ 1 \\ 0 \end{bmatrix} + z \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

We recognize that $v_p = [1, 0, 0]^T$ while $v_h = y[-1, 1, 0]^T + z[-1, 0, 1]^T$ and $\{[-1, 1, 0]^T, [-1, 0, 1]^T\}$ is a basis for the null space of A . We call y, z parameters in the solution.

We will see that null spaces play a central part in the study of eigenvectors. In fact, about half of the calculation is finding a basis for the null space of a certain matrix. So, don't be too disappointed if I don't have too many examples here. You'll work dozens of them later.

The following proposition simply summarizes what we just calculated:

Proposition 5.6.6.

Let $A \in \mathbb{R}^{m \times n}$. If the system of equations $Ax = b$ is consistent then the general solution has as many parameters as the $\dim(\text{Null}(A))$.

5.6.1 linear algebra in DEqns (optional)

A very similar story is told in differential equations. In Math 334 we spend some time unraveling the solution of $L[y] = g$ where $L = P(D)$ is an n -th order polynomial in the differentiation operator with constant coefficients. In total we learn that $y = c_1y_1 + c_2y_2 + \cdots + c_ny_n + y_p$ is the solution where y_j are the homogeneous solutions which satisfy $L[y_j] = 0$ for each $j = 1, 2, \dots, n$ and, in contrast, y_p is the so-called "particular solution" which satisfies $L[y_p] = g$. On the one hand, the results in DEqns are very different because the solutions are functions which live in the infinite-dimensional function space. However, on the other hand, $L[y] = g$ is a finite dimensional problem thanks to the fortunate fact that $\text{Null}(L) = \{f \in \mathcal{F}(\mathbb{R}) | L(f) = 0\} = \text{span}\{y_1, y_2, \dots, y_n\}$. For this reason there are n -parameters in the general solution which we typically denote by c_1, c_2, \dots, c_n in the Math 334 course. The particular solution is not found by row reduction on a matrix in DEqns⁶. Instead, we either use the annihilator method, power series techniques, or most generally the method of variation of parameters will calculate y_p . The analogy to the linear system $Av = b$ is striking:

1. $Av = b$ has solution $v = c_1v_1 + c_2v_2 + \cdots + c_kv_n + v_p$ where $v_j \in \text{Null}(A)$ and $Av_p = b$.
2. $L[y] = g$ has solution $y = c_1y_1 + c_2y_2 + \cdots + c_ky_n + y_p$ where $y_j \in \text{Null}(L)$ and $L[y_p] = g$.

The reason the DEqn $L[y] = g$ possesses such an elegant solution stems from the linearity of L . If you study nonlinear DEqns the structure is not so easily described.

⁶ok, to be fair you could use coordinate vectors of the next chapter to convert y_1, y_2, \dots, y_n to coordinate vectors and if you worked in a sufficiently large finite dimensional subspace of function space perhaps you could do a row reduction to find g , but this is not the typical calculation.

5.7 conclusions

We continue Theorem 4.8.1 from the previous chapter.

Theorem 5.7.1.

Let A be a real $n \times n$ matrix then the following are equivalent:

- (a.) A is invertible,
- (b.) $\text{rref}[A|0] = [I|0]$ where $0 \in \mathbb{R}^n$,
- (c.) $Ax = 0$ iff $x = 0$,
- (d.) A is the product of elementary matrices,
- (e.) there exists $B \in \mathbb{R}^{n \times n}$ such that $AB = I$,
- (f.) there exists $B \in \mathbb{R}^{n \times n}$ such that $BA = I$,
- (g.) $\text{rref}[A] = I$,
- (h.) $\text{rref}[A|b] = [I|x]$ for an $x \in \mathbb{R}^n$,
- (i.) $Ax = b$ is consistent for every $b \in \mathbb{R}^n$,
- (j.) $Ax = b$ has exactly one solution for every $b \in \mathbb{R}^n$,
- (k.) A^T is invertible,
- (l.) $\det(A) \neq 0$,
- (m.) Kramer's rule yields solution of $Ax = b$ for every $b \in \mathbb{R}^n$.
- (n.) $\text{Col}(A) = \mathbb{R}^{n \times 1}$,
- (o.) $\text{Row}(A) = \mathbb{R}^{1 \times n}$,
- (p.) $\text{rank}(A) = n$,
- (q.) $\text{Null}(A) = \{0\}$,
- (r.) $\nu = 0$ for A where $\nu = \dim(\text{Null}(A))$,
- (s.) the columns of A are linearly independent,
- (t.) the rows of A are linearly independent

The addition of the comments about row, column and null space are huge since these gives us easy concise tools to characterize subspaces in \mathbb{R}^n . As we've seen in this chapter we can test for linear independence and spanning all through solving particular systems. However, clever use of matrix

notations allows us to do these calculations even without explicitly writing those equations. Again, continuing Theorem 4.8.2 from the previous chapter:

Theorem 5.7.2.

Let A be a real $n \times n$ matrix then the following are equivalent:

- (a.) A is not invertible,
- (b.) $Ax = 0$ has at least one nontrivial solution.,
- (c.) there exists $b \in \mathbb{R}^n$ such that $Ax = b$ is inconsistent,
- (d.) $\det(A) = 0$,
- (e.) $\text{Null}(A) \neq \{0\}$,
- (f.) there are $\nu = \dim(\text{Null}(A))$ parameters in the general solution to $Ax = 0$,

Can you think of anything else to add here? Let me know if you think I missed something here. If it's sufficiently interesting it'll be worth some points.

Chapter 6

isomorphism and coordinate change

Functions which preserve the structure of a vector space are called linear transformations. Many important operations in calculus are linear transformations: definite integrals, differentiation even taking a limit. Many differential equations can be written as a linear transformation acting on a function space. Linear transformations which are 1-1 and onto are called isomorphisms. It turns out that all finite dimensional vector spaces of the same dimension are isomorphic. Coordinate maps are isomorphisms. In the finite dimensional case, we can always use coordinate maps to convert a linear transformation to matrix multiplication at the level of coordinate maps. We discuss how to find the matrix of a linear transformation from \mathbb{R}^n to $\mathbb{R}^{m \times 1}$. Finally we study change of basis. It turns out the matrix of a linear transformation undergoes a similarity transformation as coordinates are changed.

6.1 examples of linear transformations

Definition 6.1.1.

Let V, W be vector spaces. If a mapping $L : V \rightarrow W$ satisfies

1. $L(x + y) = L(x) + L(y)$ for all $x, y \in V$,
2. $L(cx) = cL(x)$ for all $x \in V$ and $c \in \mathbb{R}$

then we say L is a linear transformation.

We already saw many examples for the particular case $V = \mathbb{R}^2$ and $W = \mathbb{R}^2$. I'll focus on abstract vector space examples here.

Example 6.1.2. Define $L : \mathbb{R}^{m \times n} \rightarrow \mathbb{R}^{n \times m}$ by $L(A) = A^T$. This is clearly a linear transformation since

$$L(cA + B) = (cA + B)^T = cA^T + B^T = cL(A) + L(B)$$

for all $A, B \in \mathbb{R}^{m \times n}$ and $c \in \mathbb{R}$.

Example 6.1.3. Let V, W be a vector spaces and $L : V \rightarrow W$ defined by $L(x) = 0$ for all $x \in V$. This is a linear transformation known as the **trivial transformation**

$$L(x + y) = 0 = 0 + 0 = L(x) + L(y)$$

and

$$L(cx) = 0 = c0 = cL(x)$$

for all $c \in \mathbb{R}$ and $x, y \in V$.

Example 6.1.4. The identity function on a vector space is also a linear transformation. Let $Id : V \rightarrow V$ satisfy $L(x) = x$ for each $x \in V$. Observe that

$$Id(x + cy) = x + cy = x + c(y) = Id(x) + cId(y)$$

for all $x, y \in V$ and $c \in \mathbb{R}$.

Example 6.1.5. Define $L : C^0(\mathbb{R}) \rightarrow \mathbb{R}$ by $L(f) = \int_0^1 f(x)dx$. Notice that L is well-defined since all continuous functions are integrable and the value of a definite integral is a number. Furthermore,

$$L(f + cg) = \int_0^1 (f + cg)(x)dx = \int_0^1 [f(x) + cg(x)]dx = \int_0^1 f(x)dx + c \int_0^1 g(x)dx = L(f) + cL(g)$$

for all $f, g \in C^0(\mathbb{R})$ and $c \in \mathbb{R}$. The definite integral is a linear transformation.

Example 6.1.6. Let $L : C^1(\mathbb{R}) \rightarrow C^0(\mathbb{R})$ be defined by $L(f)(x) = f'(x)$ for each $f \in P_3$. We know from calculus that

$$L(f + g)(x) = (f + g)'(x) = f'(x) + g'(x) = L(f)(x) + L(g)(x)$$

and

$$L(cf)(x) = (cf)'(x) = cf'(x) = cL(f)(x).$$

The equations above hold for all $x \in \mathbb{R}$ thus we find function equations $L(f + g) = L(f) + L(g)$ and $L(cf) = cL(f)$ for all $f, g \in C^1(\mathbb{R})$ and $c \in \mathbb{R}$.

Example 6.1.7. Let $a \in \mathbb{R}$. The evaluation mapping $\phi_a : \mathcal{F}(\mathbb{R}) \rightarrow \mathbb{R}$ is defined by $\phi_a(f) = f(a)$. This is a linear transformation as $(f + cg)(a) = f(a) + cg(a)$ by definition of function addition and scalar multiplication.

Example 6.1.8. Let $T : \mathbb{R}^{n \times n} \rightarrow \mathbb{R}$ be the determinant map; $T(A) = \det(A)$. Notice this is not a linear map since we found $\det(A + B) \neq \det(A) + \det(B)$ in general. Also we know $\det(cA) = c^n \det(A)$. As I mentioned in the determinants chapter, the determinant is actually a multilinear transformation on the columns of the matrix.

Proposition 6.1.9.

Let $L : V \rightarrow W$ be a linear transformation,

1. $L(0) = 0$
2. $L(c_1v_1 + c_2v_2 + \cdots + c_nv_n) = c_1L(v_1) + c_2L(v_2) + \cdots + c_nL(v_n)$ for all $v_i \in V$ and $c_i \in \mathbb{R}$.

Proof: to prove of (1.) let $x \in V$ and notice that $x - x = 0$ thus

$$L(0) = L(x - x) = L(x) + L(-1x) = L(x) - L(x) = 0.$$

To prove (2.) we use induction on n . Notice the proposition is true for $n=1,2$ by definition of linear transformation. Assume inductively $L(c_1v_1 + c_2v_2 + \cdots + c_nv_n) = c_1L(v_1) + c_2L(v_2) + \cdots + c_nL(v_n)$ for all $v_i \in V$ and $c_i \in \mathbb{R}$ where $i = 1, 2, \dots, n$. Let $v_1, v_2, \dots, v_n, v_{n+1} \in V$ and $c_1, c_2, \dots, c_n, c_{n+1} \in \mathbb{R}$ and consider, $L(c_1v_1 + c_2v_2 + \cdots + c_nv_n + c_{n+1}v_{n+1}) =$

$$\begin{aligned} &= L(c_1v_1 + c_2v_2 + \cdots + c_nv_n) + c_{n+1}L(v_{n+1}) && \text{by linearity of } L \\ &= c_1L(v_1) + c_2L(v_2) + \cdots + c_nL(v_n) + c_{n+1}L(v_{n+1}) && \text{by the induction hypothesis.} \end{aligned}$$

Hence the proposition is true for $n+1$ and we conclude by the principle of mathematical induction that (2.) is true for all $n \in \mathbb{N}$. \square

Remark 6.1.10.

I may have neglected an induction here or there earlier. Pretty much any time I state something for n there is likely an induction lurking about. Many times in mathematics if we can state a proposition for two objects then we can just as well extend the statement for n -objects. Extended linearity of limits, derivatives, integrals, etc... all follow from (2.) since those operations are linear operations.

6.2 properties of linear transformations and coordinate maps

The theorems we proved for the case of linear transformations from \mathbb{R}^n to \mathbb{R}^m likewise transfer over to the case of a linear transformation from V to W where V, W are abstract vector spaces. For example, if $S, T \in L(V, W)$ then $S + T, S - T, cT \in L(V, W)$ for any $c \in \mathbb{R}$. If we have two abstract linear transformations say $T_1 : U \rightarrow V$ and $T_2 : V \rightarrow W$ then $T_2 \circ T_1 \in L(U, W)$. If you examine the arguments made to prove these assertions in \mathbb{R}^n you'll find we only used the axioms of a vector space as opposed to the specificities of \mathbb{R}^n . However, this is not true for statements about the matrix of the linear operator. In the abstract case we need to work with coordinate maps. I used the notation $[v]_\beta$ in the last chapter since it was sufficient. Now we need to have better notation for the coordinate maps so we can articulate the concepts clearly:

Definition 6.2.1.

Let V be a finite dimensional vector space with basis $\beta = \{v_1, v_2, \dots, v_n\}$. The coordinate map $\Phi_\beta : V \rightarrow \mathbb{R}^n$ is defined by

$$\Phi_\beta(x_1v_1 + x_2v_2 + \dots + x_nv_n) = x_1e_1 + x_2e_2 + \dots + x_ne_n$$

for all $v = x_1v_1 + x_2v_2 + \dots + x_nv_n \in V$.

This is a linear mapping, I leave the details to the reader. The next section makes use of the notation introduced here. Particularly for calculation of the matrix of an abstract linear transformation. I want to talk a little about isomorphism before I do that so I stop here for now.

6.3 isomorphism of vector spaces

A one-one correspondence is a map which is 1-1 and onto. If we can find such a mapping between two sets then it shows those sets have the same cardinality. Cardinality is a crude idea of size, it turns out that all finite dimensional vector spaces have the same cardinality. In linear algebra we will find it useful to have a way of characterizing when two vector spaces are essentially the same space. At a minimum we should expect they are in 1-1 correspondence. In addition we would like for linear combinations to be maintained. We've seen an example of this already, the coordinate mapping maintains linear combinations. This is absolutely crucial if coordinates of a vector are to completely describe it. ¹

Definition 6.3.1.

Let V, W be vector spaces then $\Phi : V \rightarrow W$ is an **isomorphism** if it is a 1-1 and onto mapping which is also a linear transformation. If there is an isomorphism between vector spaces V and W then we say those vector spaces are **isomorphic** and we denote this by $V \cong W$.

Other authors sometimes denote isomorphism by equality. But, I'll avoid that custom as I am reserving $=$ to denote set equality.

Example 6.3.2. Let $V = \mathbb{R}^3$ and $W = P_2$. Define a mapping $\Phi : P_2 \rightarrow \mathbb{R}^3$ by

$$\Phi(ax^2 + bx + c) = (a, b, c)$$

for all $ax^2 + bx + c \in P_2$. To prove this function is onto we should chose an arbitrary element in the codomain, say $(c_1, c_2, c_3) \in \mathbb{R}^3$. I think it's pretty obvious that $c_1x^2 + c_2x + c_3$ maps to (c_1, c_2, c_3) under Φ hence Φ is onto. To prove Φ is one-one, assume $\Phi(a_1x^2 + a_2x + a_3) = \Phi(b_1x^2 + b_2x + b_3)$,

$$(a_1, a_2, a_3) = (b_1, b_2, b_3) \Rightarrow a_1 = b_1, a_2 = b_2, a_3 = b_3$$

¹I assume you know what the terms "onto", "1-1", "injective", "surjective", "1-1 correspondence", "bijection" mean. I also assume you know the basic theorems for compositions and inverses of functions.

thus $a_1x^2 + a_2x + a_3 = b_1x^2 + b_2x + b_3$. Therefore, Φ is a bijection. Check for linearity,

$$\begin{aligned}\Phi(a_1x^2 + a_2x + a_3 + c(b_1x^2 + b_2x + b_3)) &= \Phi((a_1 + cb_1)x^2 + (a_2 + cb_2)x + a_3 + cb_3) \\ &= (a_1 + cb_1, a_2 + cb_2, a_3 + cb_3) \\ &= (a_1, a_2, a_3) + c(b_1, b_2, b_3) \\ &= \Phi(a_1x^2 + a_2x + a_3) + c\Phi(b_1x^2 + b_2x + b_3)\end{aligned}$$

for all $a_1x^2 + a_2x + a_3, b_1x^2 + b_2x + b_3 \in P_2$ and $c \in \mathbb{R}$. Therefore, Φ is an isomorphism and $\mathbb{R}^3 \cong P_2$. As vector spaces, \mathbb{R}^3 and polynomials of upto quadratic order are the same.

Example 6.3.3. Let $\Phi : \mathbb{R}^{m \times n} \rightarrow \mathbb{R}^{mn}$ be defined by

$$\Phi\left(\sum_{i,j} A_{ij}E_{ij}\right) = (A_{11}, \dots, A_{1n}, A_{21}, \dots, A_{2n}, \dots, A_{m1}, \dots, A_{mn})$$

This map simply takes the entries in the matrix and strings them out to a vector of length mn . I leave it to the reader to prove that Φ is an isomorphism.

Remark 6.3.4.

Notice that the two examples above basically prove that Φ is a coordinate map for the given abstract vector space. The example below examines the inverse of a coordinate map, if you think about it $\Psi^{-1} : \mathbb{R}^3 \rightarrow S_2$ gives a coordinate system on S_2 .

Example 6.3.5. Let S_2 be the set of 2×2 symmetric matrices. Let $\Psi : \mathbb{R}^3 \rightarrow S_2$ be defined by

$$\Psi(x, y, z) = \begin{bmatrix} x & y \\ y & z \end{bmatrix}$$

Notice

$$(\Psi(x, y, z))^T = \begin{bmatrix} x & y \\ y & z \end{bmatrix}^T = \begin{bmatrix} x & y \\ y & z \end{bmatrix}$$

so the function Ψ is well-defined, it actually maps where I said it should. Also, if $A = \begin{bmatrix} x & y \\ y & z \end{bmatrix} \in S_2$ clearly $\Psi(x, y, z) = A$ thus Ψ is surjective. Injectivity is also easy to verify,

$$\Psi(x, y, z) = \Psi(a, b, c) \Rightarrow \begin{bmatrix} x & y \\ y & z \end{bmatrix} = \begin{bmatrix} a & b \\ b & c \end{bmatrix} \quad x = a, y = b, z = c$$

thus $(x, y, z) = (a, b, c)$. Apparently 2×2 symmetric matrices are also the same as \mathbb{R}^3 as vector spaces.

Proposition 6.3.6.

Let V_1, V_2, V_3 be vector spaces and $\Phi : V_1 \rightarrow V_2$ and $\Psi : V_2 \rightarrow V_3$ are isomorphisms.

1. $\Phi^{-1} : V_2 \rightarrow V_1$ is an isomorphism.
2. $\Psi \circ \Phi : V_1 \rightarrow V_3$ is an isomorphism.

Proof: The inverse of a bijection is a bijection. We need only demonstrate linearity, let $x, y \in V_2$ and $c \in \mathbb{R}$. Note by surjectivity of Ψ there exist $a, b \in V_1$ such that $\Psi(a) = x$ and $\Psi(b) = y$ which means $\Psi^{-1}(x) = a$ and $\Psi^{-1}(y) = b$. Consider then

$$\begin{aligned}
 \Phi^{-1}(x + cy) &= \Phi^{-1}(\Psi(a) + c\Psi(b)) && \Psi \text{ is onto} \\
 &= \Phi^{-1}(\Psi(a + cb)) && \Psi \text{ is linear} \\
 &= a + cb && \text{defn of inverse function} \\
 &= \Psi^{-1}(x) + c\Psi^{-1}(y) && \text{defn. of } a, b.
 \end{aligned}$$

this proves (1.). To prove (2.) recall that the composition of bijections is again a bijection. Moreover, Proposition 3.3.1 proves the composition of linear transformation is a linear transformation. \square

Theorem 6.3.7.

Vector spaces with the same dimension are isomorphic.

Proof: Let V, W be a vector spaces of dimension n . It follows by definition of dimension there exists bases β_V of V and β_W of W . Moreover, we have coordinate maps with respect to each basis,

$$\Phi_{\beta_V} : V \rightarrow \mathbb{R}^n \quad \Phi_{\beta_W} : W \rightarrow \mathbb{R}^n$$

These are isomorphisms. By (1.) of Proposition 6.3.6 $\Phi_{\beta_W}^{-1}$ is an isomorphism. Observe that the map $\Phi_{\beta_W}^{-1} \circ \Phi_{\beta_V} : V \rightarrow W$ is the composition of isomorphisms and by (2.) (1.) of Proposition 6.3.6 this mapping provides an isomorphism of V and W . \square

This theorem helps affirm my contention that coordinates encapsulate the linear structure of a vector space. The technique used in this proof is also used in many discussions of abstract vector spaces. We take some idea for matrices and lift it up to the abstract vector space by the coordinate isomorphism. Then we can define things like the trace or determinant of a linear transformation. We simply define the trace or determinant of a linear transformation to be the trace or determinant of the matrix of the operator. We need to understand coordinate change a little better before we make those definitions.

Remark 6.3.8.

There is much more to say about the theory of linear operators. There are interesting theorems about invariant operators and minimal polynomials. My intent in this chapter is just to alert you to the basics and a few technical results. There is more to say. For example, $\ker(T) = \{0\}$ iff T is one-one. We saw that result in the case of \mathbb{R}^n but it just as well applies to the abstract vector space linear transformation. It's probably a useful exercise to make a list of all the important properties of linear transformations we've seen this semester. These notes lack that organizational summary at the present. If you would like to read more about polynomials in abstract linear algebra just ask me sometime, I'll point you towards a book or two.

6.4 change we can believe in (no really, no joke)

A vector space does not come with a basis. We typically **choose** a basis and work out everything in terms of that particular choice. The coordinates prescribed from our choice are but one of many choices. It is natural to inquire how the coordinates of vectors and the matrices of linear transformations change form when we begin using a different basis. Coordinate change is an important idea in physics and engineering since a correct choice of coordinates will better reveal hidden symmetries and special properties of a given system. One of the great contributions of Einstein was to emphasize that coordinates were simply a picture of an underlying coordinate independent physics. That physical principle encouraged the study of **coordinate free** geometry which is at the heart of modern differential geometry. Linear algebra is perhaps the simplest implementation of these ideas. The linear transformations are coordinate free objects which have many different matrix representations in various coordinate systems. These various representations are related according to a **similarity transformations** as described later in this section.

6.4.1 matrix of an abstract linear transformation

Let me be a little more concrete about the task before us: The standard coordinates are just one of many choices of \mathbb{R}^n , we would like to be able to find matrix representations that are consistent with nonstandard bases. In addition, it would be nice if we could find a matrix representation of a linear operator on an abstract vector space. It can't be direct since abstract vectors do not form column vectors to multiply on a matrix. For example, $f(x) = x^2 + 3x + 2 \in P_2$ but we cannot write $Df(x) = 2x + 3$ as a matrix multiplication using just polynomials. We need to make use of coordinates. Coordinates allow us to switch $x^2 + 3x + 2$ to a corresponding column vector.

Definition 6.4.1.

Let $T : V \rightarrow W$ be linear transformation between vector spaces V and W and suppose $\Phi_\beta : V \rightarrow \mathbb{R}^n$ and $\Phi_{\bar{\beta}} : W \rightarrow \mathbb{R}^{m \times 1}$ are coordinate mappings with respect to the bases $\beta, \bar{\beta}$ for V, W respectively. Given all the preceding data we define the matrix of T with respect to $\beta, \bar{\beta}$ to be $[T]_{\beta, \bar{\beta}} \in \mathbb{R}^{m \times n}$ which is defined implicitly through the equation

$$T = \Phi_{\bar{\beta}} \circ L_{[T]_{\beta, \bar{\beta}}} \circ \Phi_\beta^{-1}.$$

Or if you prefer, for each $x \in \mathbb{R}^n$

$$[T]_{\beta, \bar{\beta}} x = \Phi_{\bar{\beta}}(T(\Phi_\beta^{-1}(x)))$$

Or, you may find it easier to calculate with $\Phi_{\bar{\beta}} \circ T = L_{[T]_{\beta, \bar{\beta}}} \circ \Phi_\beta$ which suggests we calculate the matrix $[T]_{\beta, \bar{\beta}}$ by inspecting the equation:

$$[T(x)]_{\bar{\beta}} = [T]_{\beta, \bar{\beta}}[x]_{\beta}.$$

This is the technique we used in lecture a couple times. I do expect you understand the notation here. Both $[x]_\beta$ and $\Phi_\beta(x)$ and the diagrams I wrote in lecture. These diagrams guide the thinking and if you understand them the definition above is not a burden. Instead, it's a logically inevitability. In other words, it's *natural*. I elaborate on this point in the next paragraph.

Let's walk through the formula $[T]_{\beta,\bar{\beta}}x = \Phi_{\bar{\beta}}(T(\Phi_\beta^{-1}(x)))$: we begin on the RHS with a column vector x , then Φ_β^{-1} lifts the column vector up to the abstract vector $\Phi_\beta^{-1}(x)$ in V . Next we operate by T which moves us over to the vector $T(\Phi_\beta^{-1}(x))$ which is in W . Finally the coordinate map $\Phi_{\bar{\beta}}$ pushes the abstract vector in W back to a column vector $\Phi_{\bar{\beta}}(T(\Phi_\beta^{-1}(x)))$ which is in $\mathbb{R}^{m \times 1}$. The same journey is accomplished by just multiplying² x by the $m \times n$ matrix $[T]_{\beta,\bar{\beta}}$.

$$\begin{array}{ccc}
 V & \xrightarrow{T} & W \\
 \Phi_\beta^{-1} \uparrow & & \downarrow \Phi_{\bar{\beta}} \\
 \mathbb{R}^n & \xrightarrow{L_{[T]_{\beta,\bar{\beta}}}} & \mathbb{R}^n
 \end{array}$$

Proposition 6.4.2.

Given the data in the preceding definition,

$$\text{col}_i([T]_{\beta,\bar{\beta}}) = \Phi_{\bar{\beta}}(T(\Phi_\beta^{-1}(e_i))).$$

Proof: Apply Theorem 3.7.12. \square

Enough generalities, let's see how this definition is fleshed out in a concrete example.

Example 6.4.3. Let $\beta = \{1, x, x^2\}$ be the basis for P_2 and consider the derivative mapping $D : P_2 \rightarrow P_2$. Find the matrix of D assuming that P_2 has coordinates with respect to β on both copies of P_2 . Define and observe

$$\Phi(x^n) = e_{n+1} \quad \text{whereas} \quad \Phi^{-1}(e_n) = x^{n-1}$$

²remember the notation $L_{[T]_{\beta,\bar{\beta}}}$ indicates the operation of left multiplication by the matrix $[T]_{\beta,\bar{\beta}}$; that is $L_{[T]_{\beta,\bar{\beta}}}(x) = [T]_{\beta,\bar{\beta}}x$ for all x .

for $n = 0, 1, 2$. Recall $D(ax^2 + bx + c) = 2ax + bx$.

$$\begin{aligned} \text{col}_1([D]_{\beta,\beta}) &= \Phi_\beta(D(\Phi_\beta^{-1}(e_1))) = \Phi_\beta(D(1)) = \Phi_\beta(0) = 0 \\ \text{col}_2([D]_{\beta,\beta}) &= \Phi_\beta(D(\Phi_\beta^{-1}(e_2))) = \Phi_\beta(D(x)) = \Phi_\beta(1) = e_1 \\ \text{col}_3([D]_{\beta,\beta}) &= \Phi_\beta(D(\Phi_\beta^{-1}(e_3))) = \Phi_\beta(D(x^2)) = \Phi_\beta(2x) = 2e_2 \end{aligned}$$

Therefore we find,

$$[D]_{\beta,\beta} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix}.$$

Calculate D^3 . Is this surprising?

We saw this example before, but I thought it might be comforting to see it again. In the example below the coordinate maps are simply the identity maps so we don't bother to write them.

Example 6.4.4. Suppose that $L([t, x, y, z]^T) = (t + x + y + z, z - x, 0, 3t - z)^T$, find $[L]$.

$$\begin{aligned} L(e_1) &= L([1, 0, 0, 0]^T) = (1, 0, 0, 3)^T \\ L(e_2) &= L([0, 1, 0, 0]^T) = (1, -1, 0, 0)^T \\ L(e_3) &= L([0, 0, 1, 0]^T) = (1, 0, 0, 0)^T \\ L(e_4) &= L([0, 0, 0, 1]^T) = (1, 1, 0, -1)^T \end{aligned} \Rightarrow [L] = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & -1 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 3 & 0 & 0 & -1 \end{bmatrix}.$$

I invite the reader to check my answer here and see that $L(v) = [L]v$ for all $v \in \mathbb{R}^{4 \times 1}$ as claimed.

Example 6.4.5. Here we find the matrix of $T(A) = A + A^T$ with respect to $\beta = \{E_{11}, E_{12}, E_{21}, E_{22}\}$. Assume both domain and codomain are given same basis in this example.

$$T(A) = A + A^T, \quad A \in \mathbb{R}^{2 \times 2}$$

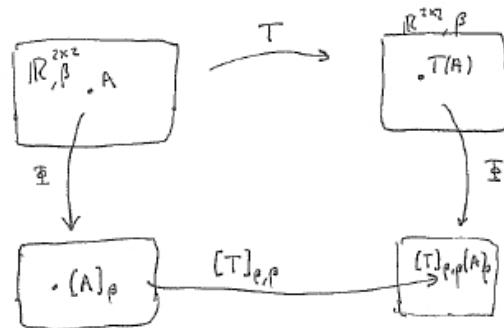
find matrix of T w.r.t. standard basis matrices
 $\beta = \{E_{11}, E_{12}, E_{21}, E_{22}\} = \{\hat{V}_1, \hat{V}_2, \hat{V}_3, \hat{V}_4\}$

$$\textcircled{1} \quad \Phi(A) = [A]_{\beta}, \quad \Phi: \mathbb{R}^{2 \times 2} \rightarrow \mathbb{R}^4$$

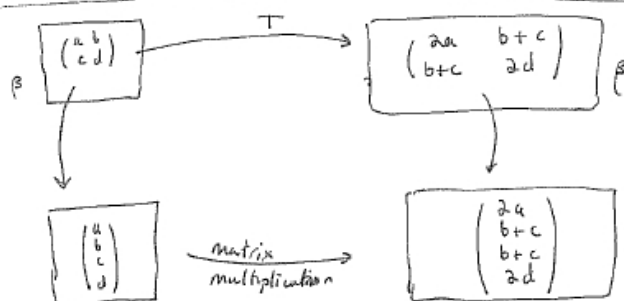
$$\textcircled{2} \quad \Phi^{-1}(\vec{V}) = \sum_{j=1}^4 v_j \hat{V}_j = v_1 E_{11} + v_2 E_{12} + v_3 E_{21} + v_4 E_{22}$$

$$\downarrow \text{def?}$$

$$= [E_{11} | E_{12} | E_{21} | E_{22}] \vec{V}$$

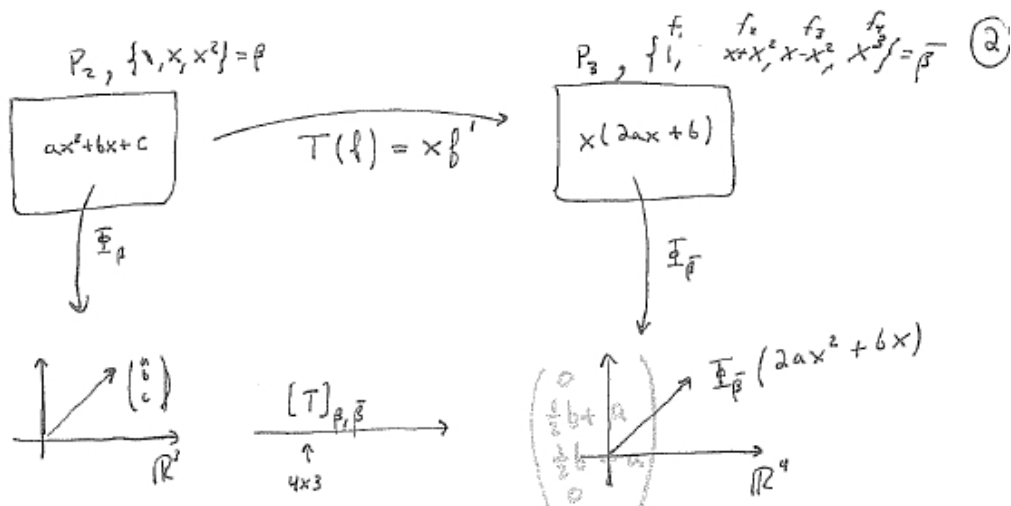


$$L_{[T]_{\beta, \beta}} = \Phi \circ T \circ \Phi^{-1}$$



$$[T]_{\beta, \beta} \begin{pmatrix} a \\ b \\ c \\ d \end{pmatrix} = \begin{bmatrix} 2 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 2 \end{bmatrix} \begin{pmatrix} a \\ b \\ c \\ d \end{pmatrix} = \begin{pmatrix} 2a \\ b+c \\ b+c \\ 2d \end{pmatrix}$$

Example 6.4.6. Again, we find the matrix for the linear transformation with respect to a pair of bases:



How to find coordinates of $2ax^2 + bx$ w.r.t $\bar{P} = \{f_1, f_2, f_3, f_4\}$?

Solve $c_1 f_1 + c_2 f_2 + c_3 f_3 + c_4 f_4 = 2ax^2 + bx$ for

c_1, c_2, c_3, c_4 in terms of a, b .

$$c_1 + (c_2 + c_3)x + (c_2 - c_3)x^2 + c_4 x^3 = 2ax^2 + bx$$

$$\therefore \begin{cases} c_1 = 0 \\ c_2 + c_3 = b \\ c_2 - c_3 = 2a \\ c_4 = 0 \end{cases} \rightarrow \begin{cases} c_2 = \frac{1}{2}(b + 2a) \\ c_3 = \frac{1}{2}(b - 2a) \end{cases}$$

$$\therefore E_{\bar{P}}(2ax^2 + bx) = \begin{bmatrix} 0 \\ b/2 + a \\ b/2 - a \\ 0 \end{bmatrix}$$

$$[T]_{\bar{P}, \bar{P}} E_P(ax^2 + bx + c) = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 1/2 & 0 \\ -1 & 1/2 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} 0 \\ b/2 + a \\ b/2 - a \\ 0 \end{bmatrix}$$

6.4.2 change of basis for linear transformations on \mathbb{R}^n

We already know how to find the matrix of a linear transformation with respect to standard bases. Finding a matrix with respect to a nonstandard basis is not much harder. We consider the case where the domain and range are the same dimension since this is the case of most interest. Since both domain and range are column vectors of the same dimension we can express the coordinate mappings and their inverses directly by a matrix multiplication.

Proposition 6.4.7.

If \mathbb{R}^n has basis $\beta = \{f_1, f_2, \dots, f_n\}$ and we denote $[\beta] = [f_1|f_2|\dots|f_n]$ then

$$\Phi_\beta(x) = [\beta]^{-1}x \quad \Phi_\beta^{-1}(y) = [\beta]y.$$

Proof: Let $v \in \mathbb{R}^n$ then $v = v_1e_1 + v_2e_2 + \dots + v_ne_n = [e_i][v]$ where e_i denote the standard basis and $[v]$ is the standard coordinate vector of v (which is the same as v in this rather special case). We also may write $v = w_1f_1 + w_2f_2 + \dots + w_nf_n = [f_i][v]_\beta$ where $[w_i] = [v]_\beta$ are the coordinates of v with respect to the basis β . Since $\{f_1, f_2, \dots, f_n\}$ form a basis the matrix $[f_i]$ is invertible and we can solve for $[v]_\beta = [f_i]^{-1}v$. Consider then,

$$\Phi_\beta(v) = [v]_\beta = [f_i]^{-1}v.$$

We find $\Phi_\beta = L_{[f_i]^{-1}}$. Since $\Phi_\beta \circ \Phi_\beta^{-1} = Id$ it follows that $[\Phi_\beta][\Phi_\beta^{-1}] = I$ thus $[\Phi_\beta]^{-1} = [\Phi_\beta^{-1}]$ and we conclude $\Phi_\beta^{-1} = L_{[f_i]}$ which means $\Phi_\beta^{-1}(y) = L_{[f_i]}(y) = [f_i]y$ for all $y \in \mathbb{R}^n$. \square

Proposition 6.4.8. *Coordinate change for vectors and linear transformations on \mathbb{R}^n .*

Let \mathbb{R}^n have bases $\beta = \{f_1, f_2, \dots, f_n\}$ and $\bar{\beta} = \{\bar{f}_1, \bar{f}_2, \dots, \bar{f}_n\}$ such that $[\beta]P = [\bar{\beta}]$ where I denoted $[\beta] = [f_1|f_2|\dots|f_n]$ and $[\bar{\beta}] = [\bar{f}_1|\bar{f}_2|\dots|\bar{f}_n]$. If $v = \sum_i v_i f_i$ and $v = \sum_j \bar{v}_j \bar{f}_j$ we denote $[v]_\beta = [v_i]$ and $[v]_{\bar{\beta}} = [\bar{v}_j]$ and the coordinate vectors of v are related by

$$[v]_{\bar{\beta}} = P^{-1}[v]_\beta$$

Moreover, if $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is a linear operator then

$$[T]_{\bar{\beta}, \bar{\beta}} = P^{-1}[T]_{\beta, \beta}P.$$

Proof: Given the data above, note we can write $\sum_i v_i f_i = [\beta][v]_\beta$ and $\sum_j \bar{v}_j \bar{f}_j = [\bar{\beta}][v]_{\bar{\beta}}$ (we can do this since we are in \mathbb{R}^n)

$$v = [\beta][v]_\beta = [\beta]PP^{-1}[v]_\beta = [\bar{\beta}]P^{-1}[v]_\beta$$

However, we also have $v = [\bar{\beta}][v]_{\bar{\beta}}$. But $[\bar{\beta}]$ is an invertible matrix thus $[\bar{\beta}][v]_{\bar{\beta}} = [\bar{\beta}]P^{-1}[v]_\beta$ implies $[v]_{\bar{\beta}} = P^{-1}[v]_\beta$.

We defined $[T]_{\bar{\beta}, \bar{\beta}}$ implicitly through the equation $T = \Phi_{\bar{\beta}}^{-1} \circ L_{[T]_{\bar{\beta}, \bar{\beta}}} \circ \Phi_{\bar{\beta}}$. In this special case the coordinate maps and their inverses are matrix multiplication as described by Proposition 6.4.7 and we calculate

$$T = L_{\bar{\beta}} \circ L_{[T]_{\bar{\beta}, \bar{\beta}}} \circ L_{\bar{\beta}^{-1}}$$

But the matrix of a composite of linear transformations is the product the matrices of those transformations, thus

$$T = L_{[\bar{\beta}][T]_{\bar{\beta}, \bar{\beta}}[\bar{\beta}]^{-1}}$$

Therefore, the standard matrix of T is $[T] = [\bar{\beta}][T]_{\bar{\beta}, \bar{\beta}}[\bar{\beta}]^{-1}$. By the same argument we find $[T] = [\beta][T]_{\beta, \beta}[\beta]^{-1}$. Thus,

$$[T] = [\bar{\beta}][T]_{\bar{\beta}, \bar{\beta}}[\bar{\beta}]^{-1} = [\beta][T]_{\beta, \beta}[\beta]^{-1} \Rightarrow [T]_{\bar{\beta}, \bar{\beta}} = [\bar{\beta}]^{-1}[\beta][T]_{\beta, \beta}[\beta]^{-1}[\bar{\beta}]$$

However, we defined P to be the matrix which satisfies $[\beta]P = [\bar{\beta}]$ thus $P = [\beta]^{-1}[\bar{\beta}]$ and $P^{-1} = [\bar{\beta}]^{-1}[\beta]$. \square .

Example 6.4.9. Let $\beta = \{[1, 1]^T, [1, -1]^T\}$ and $\gamma = \{[1, 0]^T, [1, 1]^T\}$ be bases for \mathbb{R}^2 . Find $[v]_{\beta}$ and $[v]_{\gamma}$ if $v = [2, 4]^T$. Let me frame the problem, we wish to solve:

$$v = [\beta][v]_{\beta} \quad \text{and} \quad v = [\gamma][v]_{\gamma}$$

where I'm using the basis in brackets to denote the matrix formed by concatenating the basis into a single matrix,

$$[\beta] = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \quad \text{and} \quad [\gamma] = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$$

This is the 2×2 case so we can calculate the inverse from our handy-dandy formula:

$$[\beta]^{-1} = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \quad \text{and} \quad [\gamma]^{-1} = \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix}$$

Then multiplication by inverse yields $[v]_{\beta} = [\beta]^{-1}v$ and $[v]_{\gamma} = [\gamma]^{-1}v$ thus:

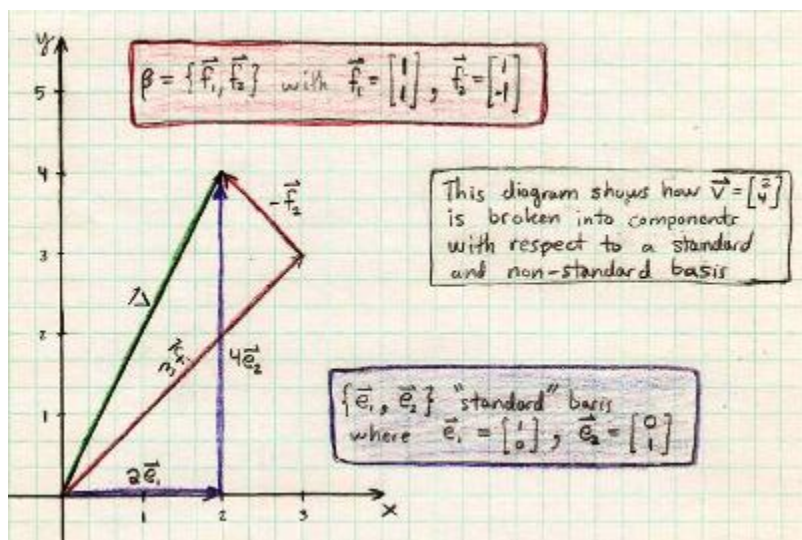
$$[v]_{\beta} = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \end{bmatrix} = \begin{bmatrix} 3 \\ -1 \end{bmatrix} \quad \text{and} \quad [v]_{\gamma} = \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \end{bmatrix} = \begin{bmatrix} -2 \\ 4 \end{bmatrix}$$

Let's verify the relation of $[v]_{\gamma}$ and $[v]_{\beta}$ relative to the change of basis matrix we denoted by P in the prop; we hope to find $[v]_{\gamma} = P^{-1}[v]_{\beta}$ (note γ is playing the role of $\bar{\beta}$ in the statement of the prop.)

$$[\beta]P = [\gamma] \Rightarrow P^{-1} = [\gamma]^{-1}[\beta] = \begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} = \begin{bmatrix} 0 & 2 \\ 1 & -1 \end{bmatrix}$$

Consider then (as a check on our calculations and also the proposition)

$$P^{-1}[v]_{\beta} = \begin{bmatrix} 0 & 2 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 3 \\ -1 \end{bmatrix} = \begin{bmatrix} -2 \\ 4 \end{bmatrix} = [v]_{\gamma} \quad \checkmark$$



Now that we've seen an example, let's find $[v]_\beta$ for an arbitrary $v = [x, y]^T$,

$$[v]_\beta = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \frac{1}{2}(x+y) \\ \frac{1}{2}(x-y) \end{bmatrix}$$

If we denote $[v]_\beta = [\bar{x}, \bar{y}]^T$ then we can understand the calculation above as the relation between the barred and standard coordinates:

$$\bar{x} = \frac{1}{2}(x+y) \quad \bar{y} = \frac{1}{2}(x-y)$$

Conversely, we can solve these for x, y to find the inverse transformations:

$$x = \bar{x} + \bar{y} \quad y = \bar{x} - \bar{y}.$$

Similar calculations are possible with respect to the γ -basis.

Example 6.4.10. Let $\bar{\beta} = \{[1, 0, 1]^T, [0, 1, 1]^T, [4, 3, 1]^T\}$. Furthermore, define a linear transformation $T: \mathbb{R}^{3 \times 1} \rightarrow \mathbb{R}^{3 \times 1}$ by the rule $T([x, y, z]^T) = [2x - 2y + 2z, x - z, 2x - 3y + 2z]^T$. Find the matrix of T with respect to the basis β . Note first that the standard basis is read from the rule:

$$T\left(\begin{bmatrix} x \\ y \\ z \end{bmatrix}\right) = \begin{bmatrix} 2x - 2y + 2z \\ x - z \\ 2x - 3y + 2z \end{bmatrix} = \begin{bmatrix} 2 & -2 & 2 \\ 1 & 0 & -1 \\ 2 & -3 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

Next, use the proposition, take $\beta = \{e_1, e_2, e_3\}$ thus $[\beta] = I_3$ and then P satisfies $I_3 P = [\bar{\beta}]$. **The change of basis matrix for changing from the standard basis to a nonstandard basis is just the matrix of the nonstandard matrix; $P = [\bar{\beta}]$** Consider then (omitting the details of

calculating P^{-1})

$$\begin{aligned}
 P^{-1}[T]P &= \begin{bmatrix} 1/3 & -2/3 & 2/3 \\ -1/2 & 1/2 & 1/2 \\ 1/6 & 1/6 & -1/6 \end{bmatrix} \begin{bmatrix} 2 & -2 & 2 \\ 1 & 0 & -1 \\ 2 & -3 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 & 4 \\ 0 & 1 & 3 \\ 1 & 1 & 1 \end{bmatrix} \\
 &= \begin{bmatrix} 1/3 & -2/3 & 2/3 \\ -1/2 & 1/2 & 1/2 \\ 1/6 & 1/6 & -1/6 \end{bmatrix} \begin{bmatrix} 4 & 0 & 4 \\ 0 & -1 & 3 \\ 4 & -1 & 1 \end{bmatrix} \\
 &= \begin{bmatrix} 4 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{bmatrix}
 \end{aligned}$$

Therefore, in the $\bar{\beta}$ -coordinates the linear operator T takes on a particularly simple form:

$$\left[T \left(\begin{bmatrix} \bar{x} \\ \bar{y} \\ \bar{z} \end{bmatrix} \right) \right]_{\bar{\beta}} = \begin{bmatrix} 4\bar{x} \\ -\bar{y} \\ \bar{z} \end{bmatrix}$$

In other words, if $\bar{\beta} = \{f_1, f_2, f_3\}$ then

$$T([\bar{x}, \bar{y}, \bar{z}]^T) = 4\bar{x}f_1 - \bar{y}f_2 + \bar{z}f_3$$

This linear transformation acts in a special way in the f_1, f_2 and f_3 directions. The basis we considered here is actually what is known as an eigenbasis for T .

We uncovered a useful formula in the proof preceding the example. Let me state it clearly for future reference

Corollary 6.4.11.

Given a linear transformation $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$ and a basis β for \mathbb{R}^n the matrix of T with respect to β is related to the standard matrix by

$$[T] = [\beta][T]_{\beta,\beta}[\beta]^{-1}$$

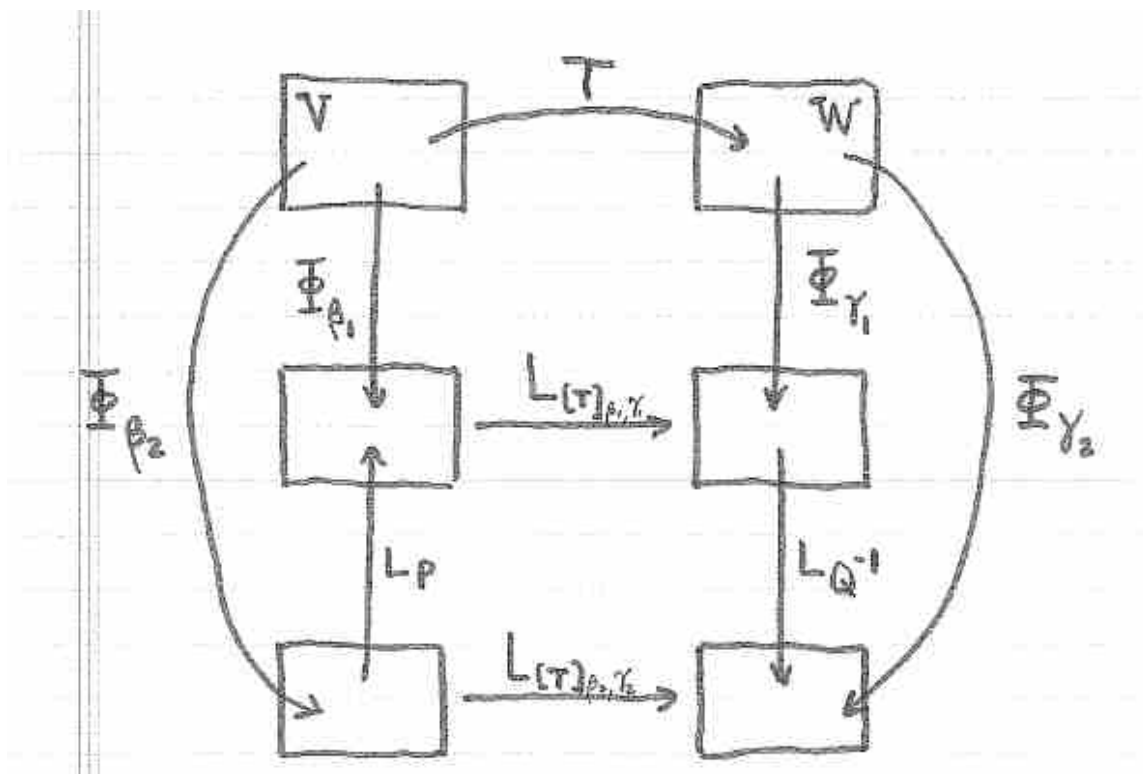
which is equivalent to stating,

$$[T]_{\beta,\beta} = [\beta]^{-1}[T][\beta]$$

If two matrices are related as $[T]$ and $[T]_{\beta,\beta}$ are related above then the matrices are similar. Something similar occurs in the abstract.

6.4.3 coordinate change of linear transformations on abstract vector spaces

In this section we will discover again some of the formulas we found in the last subsection in the special context of a linear transformation on \mathbb{R}^n . Naturally you might wonder what are the rules for coordinate change in the case the linear transformation goes between spaces of unequal dimension. We also examine how change of basis matrices are defined for abstract vector spaces. The story is not so different than the case of \mathbb{R}^n . If you understand the diagram then the rest is *just algebra*. Finally, let me just explain that coordinate change is an important topic which only finds its fullest justification once we develop further tools about eigenvectors and orthogonal bases (the next two chapters in these notes)



You can read from the diagram above that

$$L[T]_{\beta_2, \gamma_2} = \Phi_{\gamma_2} \circ \Phi_{\gamma_1}^{-1} \circ L[T]_{\beta_1, \gamma_1} \circ \Phi_{\beta_1} \circ \Phi_{\beta_2}^{-1}$$

Since the matrix of the composition of linear transformations from \mathbb{R}^n to \mathbb{R}^m is given by matrix multiplication we can simplify the above to yield ³:

$$[T]_{\beta_2, \gamma_2} = [\Phi_{\gamma_2} \circ \Phi_{\gamma_1}^{-1}][T]_{\beta_1, \gamma_1}[\Phi_{\beta_1} \circ \Phi_{\beta_2}^{-1}]$$

³in fact, this was our motivation for the definition of matrix multiplication!

here the $[\]$ notation indicates the matrix of the linear transformation with respect to the standard basis. Furthermore, note the map $\Phi_{\gamma_2} \circ \Phi_{\gamma_1}^{-1} : \mathbb{R}^{\dim(W)} \rightarrow \mathbb{R}^{\dim(W)}$ and $\Phi_{\beta_1} \circ \Phi_{\beta_2}^{-1} : \mathbb{R}^{\dim(V)} \rightarrow \mathbb{R}^{\dim(V)}$ so these are in fact linear transformations on \mathbb{R}^m or \mathbb{R}^n . This notation is a bit ugly so we like to introduce P, Q to be the change of basis matrices for V, W respective. In particular we define them by $\Phi_{\beta_1} \circ \Phi_{\beta_2}^{-1} = L_P$ and $\Phi_{\gamma_1} \circ \Phi_{\gamma_2}^{-1} = L_Q$. It follows that:

$$P = [\Phi_{\beta_1} \circ \Phi_{\beta_2}^{-1}] \quad Q^{-1} = [\Phi_{\gamma_2} \circ \Phi_{\gamma_1}^{-1}]^{-1}$$

Then we can relate the matrix of T with respect the two bases as follows:

$$[T]_{\beta_2, \gamma_2} = Q^{-1} [T]_{\beta_1, \gamma_1} P$$

I continue to use the general notation introduced here to work the examples that follow in this section. The main point of these examples is simply to demystify the discussion following the diagram on the previous page.

Example 6.4.12. .

Example: $V = P_2$, $W = \mathbb{C} = \{a+ib \mid a, b \in \mathbb{R}\}$
 $T: V \rightarrow W$ defined by $T(f) = f(i)$.

$$T(ax^2+bx+c) = ai^2+bi+c = c-a+ib$$

Coordinate maps on P_2 :

$$\Phi_{\beta_1}(ax^2+bx+c) = (a, b, c)$$

$$\beta_2 = \{1, x^2+x, x^2-x\}$$

$$ax^2+bx+c = c_1 + c_2(x^2+x) + c_3(x^2-x)$$

$$c_1 = c$$

$$\begin{aligned} c_2 + c_3 &= a \\ c_2 - c_3 &= b \end{aligned} \quad \begin{aligned} \nearrow 2c_2 &= a+b \therefore c_2 = \frac{1}{2}(a+b) \\ \searrow 2c_3 &= a-b \therefore c_3 = \frac{1}{2}(a-b) \end{aligned}$$

$$\Phi_{\beta_2}(ax^2+bx+c) = \Phi_{\beta_2}\left(c + \frac{1}{2}(a+b)(x^2+x) + \frac{1}{2}(a-b)(x^2-x)\right).$$

$$\Rightarrow \Phi_{\beta_2}(ax^2+bx+c) = \begin{bmatrix} c \\ \frac{1}{2}(a+b) \\ \frac{1}{2}(a-b) \end{bmatrix}$$

$$\begin{aligned} \Phi_{\beta_2}^{-1}\left(\begin{bmatrix} u \\ v \\ w \end{bmatrix}\right) &= u + v(x^2+x) + w(x^2-x) \\ &= u + (v+w)x^2 + (v-w)x \\ &= u + (v-w)x + (v+w)x^2 \\ &= (v+w)x^2 + (v-w)x + u. \end{aligned}$$

$$\begin{aligned} \left(\Phi_{\beta_1} \circ \Phi_{\beta_2}^{-1}\right)\begin{bmatrix} u \\ v \\ w \end{bmatrix} &= \Phi_{\beta_1}\left((v+w)x^2 + (v-w)x + u\right) \\ &= (v+w, v-w, u) \\ &= \underbrace{\begin{bmatrix} 0 & 1 & 1 \\ 0 & 1 & -1 \\ 1 & 0 & 0 \end{bmatrix}}_P \begin{bmatrix} u \\ v \\ w \end{bmatrix} \end{aligned}$$

$$\Phi_{\gamma_1}(a+ib) = (a, b), \quad \Phi_{\gamma_1}^{-1}(a, b) = a+ib$$

$$\Phi_{\gamma_2}(a+ib) = (b, a), \quad \Phi_{\gamma_2}^{-1}(a, b) = b+ai$$

$$L_{Q^{-1}} = \Phi_{\gamma_2} \circ \Phi_{\gamma_1}^{-1}$$

$$\begin{aligned} L_{Q^{-1}}\left(\begin{pmatrix} x \\ y \end{pmatrix}\right) &= \Phi_{\gamma_2}\left(\Phi_{\gamma_1}^{-1}\left(\begin{pmatrix} x \\ y \end{pmatrix}\right)\right) \\ &= \Phi_{\gamma_2}(x+iy) \\ &= (y, x) = \underbrace{\begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}}_{Q^{-1}} \begin{pmatrix} x \\ y \end{pmatrix} \end{aligned}$$

$$[T]_{\beta, \gamma_1} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} -1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \Phi_{\gamma_1}(c-a+ib) = \begin{bmatrix} c-a \\ b \\ 0 \end{bmatrix}$$

$$\therefore [T]_{\beta, \gamma_1} = \begin{bmatrix} -1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$[T]_{\beta, \gamma_2} \begin{bmatrix} c \\ \frac{1}{2}(a+b) \\ \frac{1}{2}(a-b) \end{bmatrix} = \begin{bmatrix} 0 & -1 & -1 \\ 1 & -1 & -1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} c \\ \frac{1}{2}(a+b) \\ \frac{1}{2}(a-b) \end{bmatrix} = \Phi_{\gamma_2}(c-a+ib) = \begin{bmatrix} b \\ c-a \\ 0 \end{bmatrix}$$

$$\therefore [T]_{\beta, \gamma_2} = \begin{bmatrix} 0 & -1 & -1 \\ 1 & -1 & -1 \\ 0 & 0 & 0 \end{bmatrix}$$

worked?

$$Q^{-1} [T]_{\beta, \gamma_1} P = Q^{-1} \begin{bmatrix} -1 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 1 & 1 \\ 0 & 1 & -1 \\ 1 & 0 & 0 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & -1 & -1 \\ 0 & 1 & -1 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 1 & -1 \\ 1 & -1 & -1 \end{bmatrix}$$

$$= [T]_{\beta, \gamma_2}$$

Example 6.4.13. .

Example | $T: \mathbb{R}^2 \longrightarrow \mathbb{R}^3$

$$T(x, y) = (x+y, x-y, y)$$

$$= \underbrace{\begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 0 & 1 \end{bmatrix}}_{[T]} \begin{bmatrix} x \\ y \end{bmatrix}$$

$$\beta_1 = \{e_1, 2e_2\}$$

$$\beta_2 = \{e_1 + e_2, e_1 - e_2\}$$

$$\textcircled{1} \quad \Phi_{\beta_1}(x, y) = \Phi_{\beta_1}(xe_1 + \tfrac{1}{2}y(2e_2)) = \begin{bmatrix} x \\ \tfrac{1}{2}y \end{bmatrix}$$

$$[\beta_1] = \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} \rightsquigarrow [\beta_1]^{-1} = \begin{bmatrix} 1 & 0 \\ 0 & \tfrac{1}{2} \end{bmatrix}$$

$$\Phi_{\beta_1} \begin{bmatrix} x \\ y \end{bmatrix} = [\beta_1]^{-1} \begin{bmatrix} x \\ y \end{bmatrix}. \quad \therefore \underline{\Phi_{\beta_1} = L_{[\beta_1]}^{-1}}.$$

$$\textcircled{2} \quad \Phi_{\beta_2}(x, y) = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}^{-1} \begin{bmatrix} x \\ y \end{bmatrix} = \tfrac{-1}{2} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

$$\Phi_{\beta_2}(x, y) = \begin{bmatrix} \tfrac{1}{2}(y-x) \\ \tfrac{1}{2}(x-y) \end{bmatrix}$$

CONVERSELY, $\Phi_{\beta_1}^{-1} = L_{[\beta_1]} \quad \& \quad \Phi_{\beta_2}^{-1} = L_{[\beta_2]}$

$$\text{For } \mathbb{R}^3 \begin{cases} \gamma_1 = \{e_1, 2e_2, 3e_3\} \\ \gamma_2 = \{e_3, e_2, e_1\} \end{cases}$$

$$\Phi_{\gamma_1}(x, y, z) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix}^{-1} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x \\ y/2 \\ z/3 \end{bmatrix}$$

$$\Phi_{\gamma_1} = L[\gamma_1]^{-1}, \quad L[\gamma_1] = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1/2 & 0 \\ 0 & 0 & 1/3 \end{bmatrix}$$

$$\Phi_{\gamma_2}(x, y, z) = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix}^{-1} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} z \\ y \\ x \end{bmatrix}$$

$$\hookrightarrow \Phi_{\gamma_2}(ze_3 + ye_2 + xe_1) \rightarrow$$

$$= \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix}^{-1} = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix} = L[\gamma_2]^{-1} = L[\gamma_2]$$

Consider then,

$$T(v) = [T]v \Rightarrow L[\gamma_1]^{-1}T(v) = L[\gamma_1]^{-1}[T]v \\ = \underbrace{L[\gamma_1]^{-1}[T]}_{[T]_{\beta_1, \gamma_1}} \underbrace{[\beta_1]^{-1}}_{\beta_1} v$$

$$[T]_{\beta_1, \gamma_1} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1/2 & 0 \\ 0 & 0 & 1/3 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1/2 & -1/2 \\ 0 & 1/3 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 2 \end{bmatrix} = \begin{bmatrix} 1 & 2 \\ 1/2 & -1 \\ 0 & 2/3 \end{bmatrix}$$

$$[T]_{\beta_2, \gamma_1} = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & -1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix} = L[\gamma_2]^{-1} \begin{bmatrix} 2 & 0 \\ 0 & 2 \\ 1 & -1 \end{bmatrix} = \begin{bmatrix} 1 & -1 \\ 0 & 2 \\ 2 & 0 \end{bmatrix}$$

$$[T]_{\beta_2, \gamma_2} = \underbrace{L[\gamma_2]^{-1}L[\gamma_1]}_{Q^{-1}} [T]_{\beta_1, \gamma_1} \underbrace{[\beta_1]^{-1}[\beta_2]}_P$$

The following calculation we did before, but maybe the following notation is easier to understand for some of you.

(SPECIAL CASE, $\gamma_1, \beta_1, \gamma_2, \beta_2$)
All \mathbb{R}^m or \mathbb{R}^n bases

Note:
$$[\gamma_1]^{-1}[\tau] = \underbrace{[\gamma_1]^{-1}[\tau][\beta_1][\beta_1]^{-1}}_{[\tau]_{\beta_1, \gamma_1}}$$

$$[\tau]_{\beta_1, \gamma_1} = [\gamma_1]^{-1}[\tau][\beta_1]$$

Note, then

$$\begin{aligned} [\tau]_{\beta_2, \gamma_2} &= [\gamma_2]^{-1}[\gamma_1][\tau]_{\beta_1, \gamma_1}[\beta_1][\beta_2]^{-1} \\ &= [\gamma_2]^{-1}[\gamma_1][\gamma_1]^{-1}[\tau][\beta_1][\beta_1]^{-1}[\beta_2] \\ &= [\gamma_2]^{-1}[\tau][\beta_2]. \end{aligned}$$

(consistency or use as justification for the f-la on $\mathbb{R}^n \rightarrow \mathbb{R}^m$)

Example 6.4.14. .

Example: Suppose $T: \mathbb{C} \rightarrow \mathbb{C}$ is a linear transformation with extra condition $T(\lambda v) = \lambda T(v)$. Let's examine what this condition implies for the matrix of $[T]$ with respect to the standard basis $\beta = \{1, i\}$. Here $\Phi_\beta(x+iy) = (x, y)$. Generically, any linear transformation on \mathbb{C} has

$$\begin{aligned} T(\bar{x} + i\bar{y}) &= \Phi_\beta \left(\underbrace{\begin{bmatrix} a & b \\ c & d \end{bmatrix}}_{[T]_{\beta, \beta}} \begin{bmatrix} \bar{x} \\ \bar{y} \end{bmatrix} \right) \\ &= \Phi_\beta \left(\begin{bmatrix} a\bar{x} + b\bar{y} \\ c\bar{x} + d\bar{y} \end{bmatrix} \right) \\ &= (a\bar{x} + b\bar{y}) + i(c\bar{x} + d\bar{y}) \end{aligned}$$

$$\text{Consider } \lambda v = (\alpha + i\beta)(x + iy) = \underbrace{\alpha x - \beta y}_{\bar{x}} + i \underbrace{(\alpha y + \beta x)}_{\bar{y}}$$

$$\Rightarrow T(\lambda v) = \begin{bmatrix} a(\alpha x - \beta y) + b(\alpha y + \beta x) \\ c(\alpha x - \beta y) + d(\alpha y + \beta x) \end{bmatrix} + i$$

$$\begin{aligned} \lambda T(v) &= (\alpha + i\beta)(ax + by + i(cx + dy)) \\ &= [\alpha ax + \alpha by - \beta cx - \beta dy] + i \\ &\quad + i[\beta ax + \beta by + \alpha cx + \alpha dy] \end{aligned}$$

Therefore,

$$\textcircled{\text{I}} \quad \cancel{\alpha ax} - \alpha \beta y + \cancel{b \alpha y} + \cancel{b \beta x} = \cancel{\alpha ax} + \cancel{\alpha by} - \beta cx - \beta dy$$

$$\textcircled{\text{II}} \quad \cancel{c \alpha x} - \cancel{c \beta y} + \cancel{d \alpha y} + \cancel{d \beta x} = \beta ax + \beta by + \cancel{\alpha cx} + \cancel{\alpha dy}$$

Examining ① & ② yields,

$$\textcircled{\text{I}} \quad -a\beta y + b\beta x = -\beta cx - \beta dy$$

$$\textcircled{\text{II}} \quad -c\beta y + d\beta x = \beta ax + \beta by$$

These eq^s hold $\forall \alpha, \beta, x, y$. We wish to find any necessary constraints on a, b, c, d .

$$\textcircled{\text{I}} \quad \beta = 1, x = 1, y = 0 \Rightarrow \underline{b = -c}.$$

$$\textcircled{\text{II}} \quad \beta = 1, x = 1, y = 0 \Rightarrow \underline{d = a}.$$

Hence,
$$[T]_{\mathbb{C}, \mathbb{R}} = \begin{bmatrix} a & b \\ -b & a \end{bmatrix}$$

Remark: a complex function $f: \mathbb{C} \rightarrow \mathbb{C}$ with $f(z) = u(z) + i v(z)$ is naturally represented by $\vec{f}(x, y) = (u(x, y), v(x, y))$ using the $\Phi_{\mathbb{R}}$ correspondence $\vec{f} = \Phi_{\mathbb{R}} \circ f \circ \Phi_{\mathbb{C}}^{-1}$. Differentiability of \vec{f} is shown to follow from the existence of continuously differentiable partials u_x, u_y, v_x, v_y and

$$J_{\vec{f}} = \begin{bmatrix} u_x & u_y \\ v_x & v_y \end{bmatrix} \quad (\text{Jacobian Matrix of } \vec{f})$$

Here $J_{\vec{f}}$ is matrix of the differential $D\vec{f}$ where $D_p \vec{f}(v) = J_{\vec{f}}(p)v$ and

$$\lim_{h \rightarrow 0} \frac{\|f(p+h) - f(p) - D_p \vec{f}(h)\|}{\|h\|} = 0$$

Complex Differentiability is likewise defined

$$f: \mathbb{C} \rightarrow \mathbb{C} \quad \text{has}$$

diff. df where $df: \mathbb{C} \rightarrow \mathbb{C}$ is complex linear

$$\lim_{h \rightarrow 0} \left[\frac{f(p+h) - f(p) - df(p)(h)}{h} \right] = 0.$$

The matrix of $df(p)$ with respect to $\beta = \{1, i\}$ must satisfy the requirements

$$df_p(\lambda h) = \lambda df_p(h)$$

And, we also have

$$[df_p] = \begin{bmatrix} u_x & u_y \\ v_x & v_y \end{bmatrix}.$$

However, the boxed eq^s yields

$$\boxed{u_x = v_y \quad \& \quad u_y = -v_x}$$

So, we find the Cauchy Riemann Eq^s are the consequence of the complex linearity of the complex derivative.

By the way,

$$df(p)(h) = f'(p)h = \frac{df}{dz}\bigg|_p h.$$

This algebraic result is usually clouded by analytic circumlocution. Continuous diff. of partials is a necessary but not suff. cond...

6.5 similar matrices and invariants

Definition 6.5.1.

Let $A, B \in \mathbb{R}^{n \times n}$ we say A and B are **similar matrices** if there exists an invertible matrix P such that $A = P^{-1}BP$. Moreover, we say that A is obtained from B by a **similarity transformation** if A and B are similar.

There are many nice properties for similar matrices. I'll state a few of those here but I'm leaving the proof for you. They're not too hard to prove so I figure they'll make nice Problem Set problems.

Proposition 6.5.2.

Let $A, B, C \in \mathbb{R}^{n \times n}$.

1. A is similar to A .
2. If A is similar to B then B is similar to A .
3. If A is similar to B and B is similar to C then A similar to C .
4. If A and B are similar then $\det(A) = \det(B)$
5. If A and B are similar then $\text{tr}(A) = \text{tr}(B)$
6. If A and B are similar then $\text{Col}(A) = \text{Col}(B)$ and $\text{Null}(A) = \text{Null}(B)$

Given the proposition above we can make the following definitions without ambiguity.

Definition 6.5.3.

Let $T : V \rightarrow V$ be a linear transformation on a finite-dimensional vector space V and let β be any basis of V ,

1. $\det(T) = \det([T]_{\beta, \beta})$.
2. $\text{tr}(T) = \text{tr}([T]_{\beta, \beta})$
3. $\text{rank}(T) = \text{rank}([T]_{\beta, \beta})$.

Finally, we can define analogs of the null space and column space of a matrix in the abstract. These are called the kernel and range of the linear transformation.

Definition 6.5.4.

Let $T : V \rightarrow W$ be a linear transformation then

1. $\ker(T) = T^{-1}(\{0\})$.
2. $\text{range}(T) = T(V)$

It is easy to show $\ker(T) \leq V$ and $\text{range}(T) \leq W$. Incidentally, it can be argued that every subspace is the kernel of some linear transformation. One method for arguing a given set is a subspace is simply to find a mapping which is clearly linear and happens to have the subspace in question as the kernel. The idea I describe here is an abstract algebraic idea, I have not made much effort to bring these sort of ideas to the forefront. If you would like to read a book on linear algebra from the abstract algebra perspective I highly recommend the lucid text *Abstract Linear Algebra* by Morton L. Curtis

Proposition 6.5.5.

Let $T : V \rightarrow W$ be a linear transformation then $V/\ker(T)$ is a vector space and $V/\ker(T) \cong \text{range}(T)$.

The space $V/\ker(T)$ is called a *quotient space*. It is formed from the set of cosets of $\ker(T)$. These cosets have the form $x + \ker(T)$ where $x \notin \ker(T)$. If $\ker(T)$ is a plane through the origin then the cosets are planes with the same normal but shifted off the origin. Of course, $\ker(T)$ need not be a plane, it could be the origin, a line, a volume, a hypervolume. In fact, $\ker(T) \subset V$ so ascribing geometry to $\ker(T)$ is likely misguided if you want to be literal. Remember, V could be a solution set to a DEqn or a set of polynomials, it hardly makes sense to talk about a plane of polynomials. However, we could talk about a subset of polynomials whose coordinates fill out some plane in \mathbb{R}^n . Coordinates take abstract vector spaces and convert them back to \mathbb{R}^n . Anyhow, this proposition is an example of the Fundamental Theorem of Homomorphisms from abstract algebra. In the language of Math 421, a vector space is an abelian group with respect to vector addition with an \mathbb{R} -module structure given by the scalar multiplication. A linear transformation is just a mapping which preserves addition, it is a homomorphism in abstract-algebra-speak. You might recall from Math 200 that there is a more basic theorem, any mapping induces a bijection from its fiber quotient to its range. That is at the base of all other such fundamental theorems. Category theory is the study of such generalities in mathematics. If you intend to study pure mathematics make sure to look into category theory at some point. The basic idea is that different things in math form categories. Each category permits some family of morphisms. One can then look for theorems which hold for all categories. Or, if you see a theorem in one branch of mathematics you can use category theoretic intuition to propose analogous theorems in another branch of math. This is abstraction at its core. We try to extend patterns that we know to more general patterns. The only trouble is sometimes we can get so abstract we forget where we are. This may be an argument for women in mathematics.

6.6 conclusions

Continuing Theorem 5.7.1 from the previous chapter,

Theorem 6.6.1.

Let A be a real $n \times n$ matrix then the following are equivalent:

- (a.) A is invertible,
- (b.) $rref[A|0] = [I|0]$ where $0 \in \mathbb{R}^n$,
- (c.) $Ax = 0$ iff $x = 0$,
- (d.) A is the product of elementary matrices,
- (e.) there exists $B \in \mathbb{R}^{n \times n}$ such that $AB = I$,
- (f.) there exists $B \in \mathbb{R}^{n \times n}$ such that $BA = I$,
- (g.) $rref[A] = I$,
- (h.) $rref[A|b] = [I|x]$ for an $x \in \mathbb{R}^n$,
- (i.) $Ax = b$ is consistent for every $b \in \mathbb{R}^n$,
- (j.) $Ax = b$ has exactly one solution for every $b \in \mathbb{R}^n$,
- (k.) A^T is invertible,
- (l.) $\det(A) \neq 0$,
- (m.) Kramer's rule yields solution of $Ax = b$ for every $b \in \mathbb{R}^n$.
- (n.) $Col(A) = \mathbb{R}^{n \times 1}$,
- (o.) $Row(A) = \mathbb{R}^{1 \times n}$,
- (p.) $rank(A) = n$,
- (q.) $Null(A) = \{0\}$,
- (r.) $\nu = 0$ for A where $\nu = \dim(Null(A))$,
- (s.) the columns of A are linearly independent,
- (t.) the rows of A are linearly independent,

Let A be a real $n \times n$ matrix then the following are equivalent:

- (u.) the induced linear operator L_A is onto; $L_A(\mathbb{R}^n) = \mathbb{R}^n$.
- (v.) the induced linear operator L_A is 1-1
- (w.) the induced linear operator L_A is an isomorphism.
- (x.) the kernel of the induced linear operator is trivial; $\ker(L_A) = \{0\}$.

Again, we should pay special attention to the fact that the above comments hold only for a square matrix. If we consider a rectangular matrix then the connection between the concepts in the theorem are governed by the dimension formulas we discovered in the previous chapter.

Next, continuing Theorem 5.7.2 from the previous chapter:

Theorem 6.6.2.

Let A be a real $n \times n$ matrix then the following are equivalent:

- (a.) A is not invertible,
- (b.) $Ax = 0$ has at least one nontrivial solution.,
- (c.) there exists $b \in \mathbb{R}^n$ such that $Ax = b$ is inconsistent,
- (d.) $\det(A) = 0$,
- (e.) $\text{Null}(A) \neq \{0\}$,
- (f.) there are $\nu = \dim(\text{Null}(A))$ parameters in the general solution to $Ax = 0$,
- (g.) the induced linear operator L_A is **not** onto; $L_A(\mathbb{R}^n) \neq \mathbb{R}^n$.
- (h.) the induced linear operator L_A is **not** 1-1
- (i.) the induced linear operator L_A is **not** an isomorphism.
- (j.) the kernel of the induced linear operator is **nontrivial**; $\ker(L_A) \neq \{0\}$.

Can you think of anything else to add here? Let me know if you think I missed something here. If it's sufficiently interesting it'll be worth some points.

Chapter 7

eigenvalues and eigenvectors

The terms eigenvalue and vector originate from the German school of mathematics which was very influential in the early 20-th century. Heisenberg's formulation of quantum mechanics gave new importance to linear algebra and in particular the algebraic structure of matrices. In finite dimensional quantum systems the symmetries of the system were realized by linear operators. These operators acted on states of the system which formed a complex vector space called Hilbert Space. ¹

Operators representing momentum, energy, spin or angular momentum operate on a physical system represented by a sum of eigenfunctions. The eigenvalues then account for possible value which could be measured in an experiment. Generally, quantum mechanics involves complex vector spaces and infinite dimensional vector spaces however many of the mathematical difficulties are already present in our study of linear algebra. For example, one important question is how does one pick a set of states which diagonalize an operator? Moreover, if one operator is diagonalized by a particular basis then can a second operator be diagonalized simultaneously? Linear algebra, and in particular eigenvectors help give an answer for these questions. ²

Beyond, or perhaps I should say before, quantum mechanics eigenvectors have great application in classical mechanics, optics, population growth, systems of differential equations, chaos theory, difference equations and much much more. They are a fundamental tool which allow us to pick apart a matrix into its very core. Diagonalization of matrices almost always allow us to see the nature of a system more clearly.

However, not all matrices are diagonalizable. It turns out that any matrix is similar to a Jordan Block matrix. Moreover, the similarity transformation is accomplished via a matrix formed from concatenating generalized eigenvectors. When there are enough ordinary eigenvectors then the

¹Hilbert Spaces and infinite dimensional linear algebra are typically discussed in graduate linear algebra and/or the graduate course in functional analysis, we focus on the basics in this course.

²in addition to linear algebra one should also study group theory. In particular, matrix Lie groups and their representation theory explains most of what we call "chemistry". Magic numbers, electronic numbers, etc... all of these are eigenvalues which label the states of the so-called Casimir operators

Jordan Form of the matrix is actually a diagonal matrix. The general theory for Jordan Forms, in particular the proof of the existence of a Jordan Basis, is rather involved. I will forego typical worries about existence and just show you a few examples. I feel this is important because the Jordan Form actually does present itself in applications.

In my Chapter 9 (which I'm covering lightly this semester) we explore how eigenvectors and the Jordan form are connected to solutions of systems of differential equations. The double root solution for constant coefficient 2nd order ODEs actually has the Jordan form hiding in the details. The matrix exponential allows for elegant solutions of any system of differential equations. My approach is similar to that given in the text on DEqns by Nagel, Saff and Snider (the text for math 334). However, I should mention that if you wish to understand generalized eigenvectors and Jordan forms in the abstract then you should really engage in a serious study of modules. If you build a vector space over a ring instead of a field then you get a module. Many of the same theorems hold, if you are interested I would be happy to point you to some sources to begin reading. I would be a good topic for an independent study to follow this course.

Finally, there is the case of complex eigenvalues and complex eigenvectors. These have use in the real case. A general principle for linear systems is that if a complex system has a solution then the corresponding real system will inherit two solutions from the real and imaginary parts of the complex solution. Complex eigenvalues abound in applications. For example, rotation matrices have complex eigenvalues. We'll find that complex eigenvectors are useful and not much more trouble than the real case. The diagonalization provided from complex eigenvectors provides a factorization of the matrix into complex matrices. We examine how to convert such factorizations in terms of rotations. (this is one of the reasons I really like the text by Lay, his treatment of these matters on page 338-340 really helps us understand what complex e-vectors are doing for real matrices, although, it seems he only treats the 2×2 case)).

7.1 why eigenvectors?

In this section I attempt to motivate why eigenvectors are natural to study for both mathematical and physical reasons. In fact, you probably could write a book just on this question.

7.1.1 quantum mechanics

Physically measurable quantities are described by operators and states in quantum mechanics³. The operators are linear operators and the states are usually taken to be the eigenvectors with respect to a physical quantity of interest. For example:

$$\hat{p}|p\rangle = p|p\rangle \quad \hat{J}^2|j\rangle = j(j+1)|j\rangle \quad \hat{H}|E\rangle = E|E\rangle$$

³you can skip this if you're not a physics major, but maybe you're interested despite the lack of direct relevance to your major. Maybe your interested in an education not a degree. I believe this is possible so I write these words

In the above the eigenvalues were $p, j(j+1)$ and E . Physically, p is the momentum, $j(j+1)$ is the value of the square of the magnitude of the total angular momentum and E is the energy. The exact mathematical formulation of the eigenstates of momentum, energy and angular momentum is in general a difficult problem and well-beyond the scope of the mathematics we cover this semester. You have to study Hilbert space which is an infinite-dimensional vector space with rather special properties. In any event, if the physical system has nice boundary conditions then the quantum mechanics gives mathematics which is within the reach of undergraduate linear algebra. For example, one of the very interesting aspects of quantum mechanics is that we can only measure a certain pairs of operators simultaneously. Such operators have eigenstates which are simultaneously eigenstates of both operators at once. The careful study of how to label states with respect to the energy operator (called the Hamiltonian) and some other commuting symmetry operator (like isospin or angular momentum etc...) gives rise to what we call Chemistry. In other words, Chemistry is largely the tabulation of the specific interworkings of eigenstates as they correlate to the energy, momentum and spin operators (this is a small part of what is known as *representation theory* in modern mathematics). I may ask a question about simultaneous diagonalization. This is a hard topic compared to most we study.

7.1.2 stochastic matrices

Definition 7.1.1.

Let $P \in \mathbb{R}^{n \times n}$ with $P_{ij} \geq 0$ for all i, j . If the sum of the entries in any column of P is one then we say P is a stochastic matrix.

Example 7.1.2. Stochastic Matrix: A medical researcher⁴ is studying the spread of a virus in 1000 lab. mice. During any given week it's estimated that there is an 80% probability that a mouse will overcome the virus, and during the same week there is an 10% likelihood a healthy mouse will become infected. Suppose 100 mice are infected to start, (a.) how many sick next week? (b.) how many sick in 2 weeks? (c.) after many many weeks what is the steady state solution?

$$\begin{array}{l} I_k = \text{infected mice at beginning of week } k \\ N_k = \text{noninfected mice at beginning of week } k \end{array} \quad P = \begin{bmatrix} 0.2 & 0.1 \\ 0.8 & 0.9 \end{bmatrix}$$

We can study the evolution of the system through successive weeks by multiply the state-vector $X_k = [I_k, N_k]$ by the probability transition matrix P given above. Notice we are given that $X_1 = [100, 900]^T$. Calculate then,

$$X_2 = \begin{bmatrix} 0.2 & 0.1 \\ 0.8 & 0.9 \end{bmatrix} \begin{bmatrix} 100 \\ 900 \end{bmatrix} = \begin{bmatrix} 110 \\ 890 \end{bmatrix}$$

After one week there are 110 infected mice Continuing to the next week,

$$X_3 = \begin{bmatrix} 0.2 & 0.1 \\ 0.8 & 0.9 \end{bmatrix} \begin{bmatrix} 110 \\ 890 \end{bmatrix} = \begin{bmatrix} 111 \\ 889 \end{bmatrix}$$

⁴this example and most of the other applied examples in these notes are borrowed from my undergraduate linear algebra course taught from Larson's text by Dr. Terry Anderson of Appalachian State University

After two weeks we have 111 mice infected. What happens as $k \rightarrow \infty$? Generally we have $X_k = PX_{k-1}$. Note that as k gets large there is little difference between k and $k-1$, in the limit they both tend to infinity. We define the steady-state solution to be $X^* = \lim_{k \rightarrow \infty} X_k$. Taking the limit of $X_k = PX_{k-1}$ as $k \rightarrow \infty$ we obtain the requirement $X^* = PX^*$. In other words, the steady state solution is found from solving $(P - I)X^* = 0$. For the example considered here we find,

$$(P - I)X^* = \begin{bmatrix} -0.8 & 0.1 \\ 0.8 & -0.1 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = 0 \quad v = 8u \quad X^* = \begin{bmatrix} u \\ 8u \end{bmatrix}$$

However, by conservation of mice, $u + v = 1000$ hence $9u = 1000$ and $u = 111.\bar{1}$ thus the steady state can be shown to be $X^* = [111.\bar{1}, 888.\bar{8}]$

Example 7.1.3. Diagonal matrices are nice: Suppose that demand for doorknobs halves every week while the demand for yo-yos it cut to $1/3$ of the previous week's demand every week due to an amazingly bad advertising campaign⁵. At the beginning there is demand for 2 doorknobs and 5 yo-yos.

$$\begin{array}{l} D_k = \text{demand for doorknobs at beginning of week } k \\ Y_k = \text{demand for yo-yos at beginning of week } k \end{array} \quad P = \begin{bmatrix} 1/2 & 0 \\ 0 & 1/3 \end{bmatrix}$$

We can study the evolution of the system through successive weeks by multiply the state-vector $X_k = [D_k, Y_k]$ by the transition matrix P given above. Notice we are given that $X_1 = [2, 5]^T$. Calculate then,

$$X_2 = \begin{bmatrix} 1/2 & 0 \\ 0 & 1/3 \end{bmatrix} \begin{bmatrix} 2 \\ 5 \end{bmatrix} = \begin{bmatrix} 1 \\ 5/3 \end{bmatrix}$$

Notice that we can actually calculate the k -th state vector as follows:

$$X_k = P^k X_1 = \begin{bmatrix} 1/2 & 0 \\ 0 & 1/3 \end{bmatrix}^k \begin{bmatrix} 2 \\ 5 \end{bmatrix} = \begin{bmatrix} 2^{-k} & 0 \\ 0 & 3^{-k} \end{bmatrix}^k \begin{bmatrix} 2 \\ 5 \end{bmatrix} = \begin{bmatrix} 2^{-k+1} \\ 5(3^{-k}) \end{bmatrix}$$

Therefore, assuming this silly model holds for 100 weeks, we can calculate the 100-the step in the process easily,

$$X_{100} = P^{100} X_1 = \begin{bmatrix} 2^{-101} \\ 5(3^{-100}) \end{bmatrix}$$

Notice that for this example the analogue of X^* is the zero vector since as $k \rightarrow \infty$ we find X_k has components which both go to zero.

For some systems we'll find a special state we called the "steady-state" for the system. If the system was attracted to some particular final state as $t \rightarrow \infty$ then that state satisfied $PX^* = X^*$. We will learn in this chapter to identify this makes X^* is an eigenvector of P with eigenvalue 1.

⁵insert your own more interesting set of quantities that doubles/halves or triples during some regular interval of time

7.1.3 motion of points under linear transformations

Remark 7.1.4.

What follows here is just intended to show you how you might stumble into the concept of an eigenvector even if you didn't set out to find it. The calculations we study here are not what we aim to ultimately dissect in this chapter. This is purely a mathematical experiment to show how eigenvectors arise naturally through repeated matrix multiplication on a given point. Physically speaking the last two subsections were way more interesting.

I'll focus on two dimensions to begin for the sake of illustration. Let's take a matrix A and a point x_o and study what happens as we multiply by the matrix. We'll denote $x_1 = Ax_o$ and generally $x_{k+1} = Ax_k$. It is customary to call x_k the " k -th state of the system". As we multiply the k -th state by A we generate the $k + 1$ -th state.⁶

Example 7.1.5. Let $A = \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix}$ and let $x_o = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$. Calculate,

$$\begin{aligned} x_1 &= \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 3 \\ 6 \end{bmatrix} \\ x_2 &= \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix} \begin{bmatrix} 3 \\ 6 \end{bmatrix} = \begin{bmatrix} 9 \\ 18 \end{bmatrix} \\ x_3 &= \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix} \begin{bmatrix} 9 \\ 18 \end{bmatrix} = \begin{bmatrix} 27 \\ 54 \end{bmatrix} \\ x_4 &= \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix} \begin{bmatrix} 27 \\ 54 \end{bmatrix} = \begin{bmatrix} 81 \\ 162 \end{bmatrix} \end{aligned}$$

Each time we multiply by A we scale the vector by a factor of three. If you want to look at x_o as a point in the plane the matrix A pushes the point x_k to the point $x_{k+1} = 3x_k$. Its not hard to see that $x_k = 3^k x_o$. What if we took some other point, say $y_o = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ then what will A do?

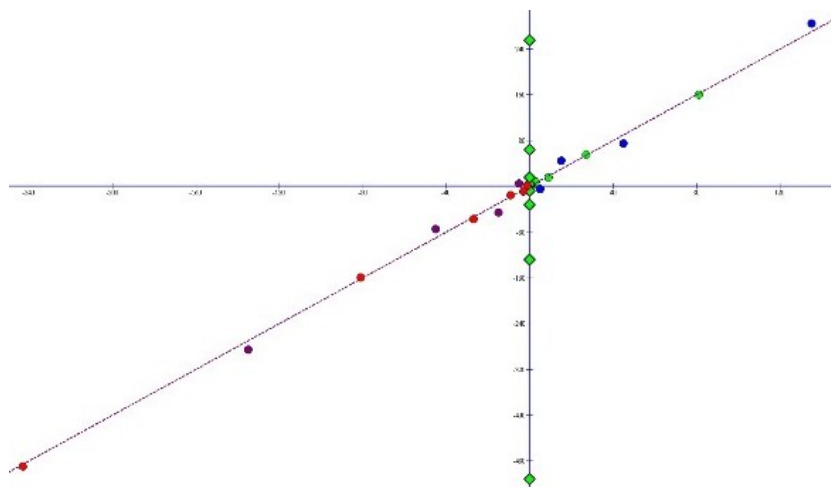
$$\begin{aligned} y_1 &= \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 3 \\ 8 \end{bmatrix} \\ y_2 &= \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix} \begin{bmatrix} 3 \\ 8 \end{bmatrix} = \begin{bmatrix} 9 \\ 16 \end{bmatrix} \\ y_3 &= \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix} \begin{bmatrix} 9 \\ 16 \end{bmatrix} = \begin{bmatrix} 27 \\ 56 \end{bmatrix} \\ y_4 &= \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix} \begin{bmatrix} 27 \\ 48 \end{bmatrix} = \begin{bmatrix} 81 \\ 160 \end{bmatrix} \end{aligned}$$

Now, what happens for arbitrary k ? Can you find a formula for y_k ? This point is not as simple as x_o . The vector x_o is apparently a special vector for this matrix. Next study, $z_o = \begin{bmatrix} 0 \\ 2 \end{bmatrix}$,

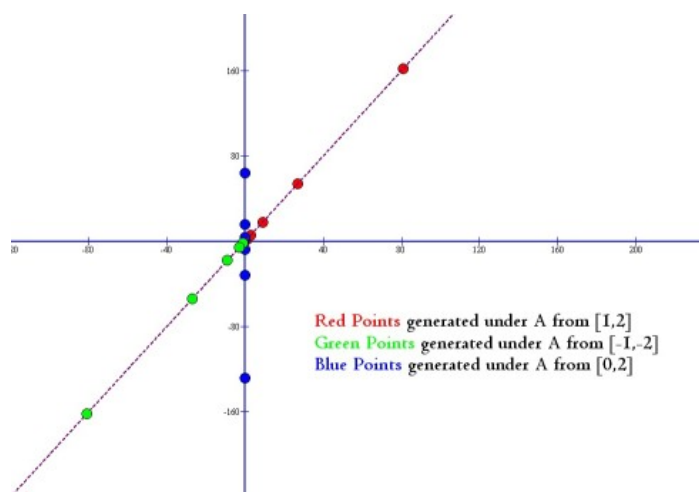
$$\begin{aligned} z_1 &= \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix} \begin{bmatrix} 0 \\ 2 \end{bmatrix} = \begin{bmatrix} 0 \\ -2 \end{bmatrix} \\ z_2 &= \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix} \begin{bmatrix} 0 \\ -2 \end{bmatrix} = \begin{bmatrix} 0 \\ 4 \end{bmatrix} \\ z_3 &= \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix} \begin{bmatrix} 0 \\ 4 \end{bmatrix} = \begin{bmatrix} 0 \\ -8 \end{bmatrix} \\ z_4 &= \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix} \begin{bmatrix} 0 \\ -8 \end{bmatrix} = \begin{bmatrix} 0 \\ 16 \end{bmatrix} \end{aligned}$$

Let me illustrate what is happening with a picture. I have used color to track the motion of a particular point. You can see that all points tend to get drawn into the line with direction vector x_o with the sole exception of the points along the y -axis which I have denoted via diamonds in the picture below:

⁶ask Dr. Mavinga and he will show you how a recursively defined linear difference equation can be converted into a matrix equation of the form $x_{k+1} = Ax_k$, this is much the same idea as saying that an n -th order ODE can be converted into a system of n - first order ODEs.



The directions $[1, 2]$ and $[0, 1]$ are special, the following picture illustrates the motion of those points under A :



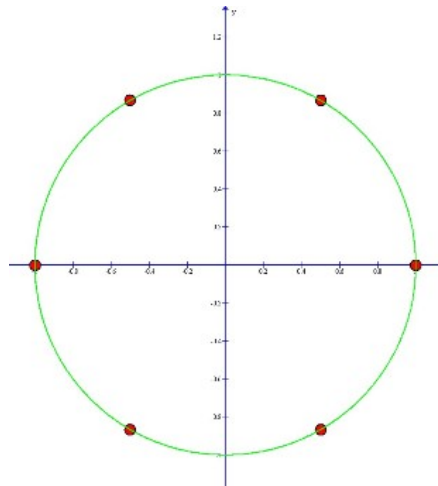
The line with direction vector $[1, 2]$ seems to attract almost all states to itself. On the other hand, if you could imagine yourself a solution walking along the y -axis then if you took the slightest mis-step to the right or left then before another dozen or so steps you'd find yourself stuck along the line in the $[1, 2]$ -direction. There is a connection of the system $x_{k+1} = Ax_k$ and the system of differential equations $dx/dt = Bx$ if we have $B = I + A$. Perhaps we'll have time to explore the questions posed in this example from the viewpoint of the corresponding system of differential equations. In this case the motion is very discontinuous. I think you can connect the dots here to get a rough picture of what the corresponding system's solutions look like. In the differential equations Chapter we develop these ideas a bit further. For now we are simply trying to get a feeling for how one might discover that there are certain special vector(s) associated with a given matrix. We call these vectors the "eigenvectors" of A .

The next matrix will generate rather different motions on points in the plane.

Example 7.1.6. Let $A = \begin{bmatrix} \frac{1}{2} & \frac{\sqrt{3}}{2} \\ -\frac{\sqrt{3}}{2} & \frac{1}{2} \end{bmatrix}$. Consider the trajectory of $x_0 = [1, 0]^T$,

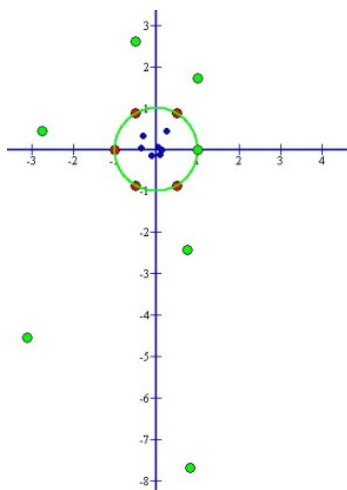
$$\begin{aligned} x_1 &= \begin{bmatrix} \frac{1}{2} & -\frac{\sqrt{3}}{2} \\ \frac{\sqrt{3}}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} \frac{1}{2} \\ \frac{\sqrt{3}}{2} \end{bmatrix} \\ x_2 &= \begin{bmatrix} \frac{1}{2} & -\frac{\sqrt{3}}{2} \\ \frac{\sqrt{3}}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} \frac{1}{2} \\ \frac{\sqrt{3}}{2} \end{bmatrix} = \begin{bmatrix} -\frac{1}{2} \\ \frac{\sqrt{3}}{2} \end{bmatrix} \\ x_3 &= \begin{bmatrix} \frac{1}{2} & -\frac{\sqrt{3}}{2} \\ \frac{\sqrt{3}}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} -\frac{1}{2} \\ \frac{\sqrt{3}}{2} \end{bmatrix} = \begin{bmatrix} -1 \\ 0 \end{bmatrix} \\ x_4 &= \begin{bmatrix} \frac{1}{2} & -\frac{\sqrt{3}}{2} \\ \frac{\sqrt{3}}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} -1 \\ 0 \end{bmatrix} = \begin{bmatrix} -\frac{1}{2} \\ -\frac{\sqrt{3}}{2} \end{bmatrix} \\ x_5 &= \begin{bmatrix} \frac{1}{2} & -\frac{\sqrt{3}}{2} \\ \frac{\sqrt{3}}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} -\frac{1}{2} \\ -\frac{\sqrt{3}}{2} \end{bmatrix} = \begin{bmatrix} \frac{1}{2} \\ -\frac{\sqrt{3}}{2} \end{bmatrix} \\ x_6 &= \begin{bmatrix} \frac{1}{2} & -\frac{\sqrt{3}}{2} \\ \frac{\sqrt{3}}{2} & \frac{1}{2} \end{bmatrix} \begin{bmatrix} \frac{1}{2} \\ -\frac{\sqrt{3}}{2} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \end{aligned}$$

Past this point we just cycle back to the same points, clearly $x_k = x_{k+6}$ for all $k \geq 0$. If we started with a different initial point we would find this pattern again. The reason for this is that A is the matrix which rotates vectors by $\pi/3$ radians. The trajectories generated by this matrix are quite different then the preceding example, there is no special direction in this case.



Although, generally this type of matrix generates elliptical orbits and then there are two special directions. Namely the major and minor axis of the elliptical orbits. Finally, this sort of matrix could have a scaling factor built in so that the trajectories spiral in or out of the origin. I provide a picture illustrating the various possibilities. The red dots in the picture below are generated from A as

was given in the preceding example, the blue dots are generated from the matrix $[\frac{1}{2}\text{col}_1(A)|\text{col}_2(A)]$ whereas the green dots are obtained from the matrix $[2\text{col}_1(A)|\text{col}_2(A)]$. In each case I started with the point $(1, 0)$ and studied the motion of the point under repeated multiplications of matrix:



Let's summarize our findings so far: if we study the motion of a given point under successive multiplications of a matrix it may be pushed towards one of several directions or it may go in a circular/spiral-type motion.

7.2 eigenvector foundations

The preceding section was motivational. We now begin the real⁷ material. Given our experience on coordinate change in the preceding chapter it should begin to be clear to you that the fundamental objects of linear algebra are linear transformations. A matrix usually give us just one picture of a more fundamental concept which is stated in terms of linear transformations and vector spaces. In view of this wisdom we cast the definition of the eigenvalue and vector in terms of an abstract linear transformation on a vector space.

Definition 7.2.1.

Let $T : V \rightarrow V$ be a linear transformation on a vector space V . If there exists $v \in V$ such that $v \neq 0$ such that $T(v) = \lambda v$ for some constant λ then we say v is an **eigenvector** of T with **eigenvalue** λ .

Usually we work with real vector spaces so the scalar λ is taken from \mathbb{R} , however it is both interesting and useful to consider the extension to \mathbb{C} . We do so at the conclusion of this chapter. For now let me just introduce a little language. If $\lambda \in \mathbb{R}$ then I say λ is a **real eigenvalue with real eigenvector** v . On the other hand, my typical notation is that if $\lambda = \alpha + i\beta \in \mathbb{C}$ with $\beta \neq 0$ then I say λ is a **complex eigenvalue with complex eigenvector** $v = a + ib$.

Example 7.2.2. Let $T(f) = Df$ where D is the derivative operator. This defines a linear transformation on function space \mathcal{F} . An eigenvector for T would be a function which is proportional to its own derivative function... in other words solve $\frac{dy}{dt} = \lambda y$. Separation of variables yields $y = ce^{\lambda t}$. The eigenfunctions for T are simply exponential functions.

Example 7.2.3. Let $T(A) = A^T$ for $A \in \mathbb{R}^{n \times n}$. To find an eigenvector for T we want a matrix $V \in \mathbb{R}^{n \times n}$ and a constant λ such that $T(V) = V^T = \lambda V$. An obvious choice is $\lambda = 1$ and choose a symmetric matrix V so $V^T = V$. Another slightly less obvious guess exists. Can you think of it?

Notice that there are infinitely many eigenvectors for a given eigenvalue in both of the examples above. The number of eigenvalues for the function space example is infinite since any $\lambda \in \mathbb{R}$ will do. On the other hand, the matrix example only had two eigenvalues. The distinction between these examples is that function space is infinite dimensional whereas the matrix example is finite-dimensional. For the most part we focus on less abstract eigenvector examples. The following definition dovetails with our definition above if you think about $L_A : \mathbb{R}^n \rightarrow \mathbb{R}^n$. An eigenvector of L_A is an eigenvector of A if we accept the definition that follows:

Definition 7.2.4.

Let $A \in \mathbb{R}^{n \times n}$. If $v \in \mathbb{R}^n$ is **nonzero** and $Av = \lambda v$ for some $\lambda \in \mathbb{C}$ then we say v is an **eigenvector** with **eigenvalue** λ of the matrix A .

We identify that the eigenvectors of A pointed in the direction where trajectories were asymptotically attracted in the examples of the preceding section. Although, the case of the circular

⁷I should mention that your text insists that e-vectors have real e-values. I make no such restriction. If we want to insist the e-values are real I will say that explicitly.

trajectories broke from that general pattern. We'll discover those circular orbits correspond to the complex case.

Our goal at this point is to find a clear and concise method to calculate eigenvalues and their corresponding eigenvector(s). Fortunately, we soon find that guessing and solving differential equations are not the usual method to calculate eigenvectors (at least not in Math 321)

Proposition 7.2.5.

Let $A \in \mathbb{R}^{n \times n}$ then λ is an eigenvalue of A iff $\det(A - \lambda I) = 0$. We say $P(\lambda) = \det(A - \lambda I)$ the **characteristic polynomial** and $\det(A - \lambda I) = 0$ is the **characteristic equation**.

Proof: Suppose λ is an eigenvalue of A then there exists a nonzero vector v such that $Av = \lambda v$ which is equivalent to $Av - \lambda v = 0$ which is precisely $(A - \lambda I)v = 0$. Notice that $(A - \lambda I)0 = 0$ thus the matrix $(A - \lambda I)$ is singular as the equation $(A - \lambda I)x = 0$ has more than one solution. Consequently $\det(A - \lambda I) = 0$.

Conversely, suppose $\det(A - \lambda I) = 0$. It follows that $(A - \lambda I)$ is singular. Clearly the system $(A - \lambda I)x = 0$ is consistent as $x = 0$ is a solution hence we know there are infinitely many solutions. In particular there exists at least one vector $v \neq 0$ such that $(A - \lambda I)v = 0$ which means the vector v satisfies $Av = \lambda v$. Thus v is an eigenvector with eigenvalue λ for A ⁸. \square

Let's collect the observations of the above proof for future reference.

Proposition 7.2.6.

The following are equivalent for $A \in \mathbb{R}^{n \times n}$ and $\lambda \in \mathbb{C}$,

1. λ is an eigenvalue of A
2. there exists $v \neq 0$ such that $Av = \lambda v$
3. there exists $v \neq 0$ such that $(A - \lambda I)v = 0$
4. λ is a solution to $\det(A - \lambda I) = 0$
5. $(A - \lambda I)v = 0$ has infinitely many solutions.

7.2.1 characteristic equations

Example 7.2.7. Let $A = \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix}$. Find the eigenvalues of A from the characteristic equation:

$$\det(A - \lambda I) = \det \begin{bmatrix} 3 - \lambda & 0 \\ 8 & -1 - \lambda \end{bmatrix} = (3 - \lambda)(-1 - \lambda) = (\lambda + 1)(\lambda - 3) = 0$$

⁸It is worth mentioning that the theorems on uniqueness of solution and singular matrices and determinant hold for linear systems with complex coefficients and variables. We don't need a separate argument for the complex case

Hence the eigenvalues are $\lambda_1 = -1$ and $\lambda_2 = 3$. Notice this is precisely the factor of 3 we saw scaling the vector in the first example of the preceding section.

Example 7.2.8. Let $A = \begin{bmatrix} \frac{1}{2} & \frac{\sqrt{3}}{2} \\ -\frac{\sqrt{3}}{2} & \frac{1}{2} \end{bmatrix}$. Find the eigenvalues of A from the characteristic equation:

$$\det(A - \lambda I) = \det \begin{bmatrix} \frac{1}{2} - \lambda & \frac{\sqrt{3}}{2} \\ -\frac{\sqrt{3}}{2} & \frac{1}{2} - \lambda \end{bmatrix} = (\frac{1}{2} - \lambda)^2 + \frac{3}{4} = (\lambda - \frac{1}{2})^2 + \frac{3}{4} = 0$$

Well how convenient is that? The determinant completed the square for us. We find: $\lambda = \frac{1}{2} \pm i\frac{\sqrt{3}}{2}$. It would seem that elliptical orbits somehow arise from complex eigenvalues

Proposition 4.3.3 proved that taking the determinant of a triangular matrix was easy. We just multiply the diagonal entries together. This has interesting application in our discussion of eigenvalues.

Example 7.2.9. Given A below, find the eigenvalues. Use Proposition 4.3.3 to calculate the determinant,

$$A = \begin{bmatrix} 2 & 3 & 4 \\ 0 & 5 & 6 \\ 0 & 0 & 7 \end{bmatrix} \Rightarrow \det(A - \lambda I) = \begin{bmatrix} 2 - \lambda & 3 & 4 \\ 0 & 5 - \lambda & 6 \\ 0 & 0 & 7 - \lambda \end{bmatrix} = (2 - \lambda)(5 - \lambda)(7 - \lambda)$$

Therefore, $\lambda_1 = 2, \lambda_2 = 5$ and $\lambda_3 = 7$.

Remark 7.2.10. *eigenwarning*

Calculation of eigenvalues does not need to be difficult. However, I urge you to be careful in solving the characteristic equation. More often than not I see students make a mistake in calculating the eigenvalues. If you do that wrong then the eigenvector calculations will often turn into inconsistent equations. This should be a clue that the eigenvalues were wrong, but often I see what I like to call the "principle of minimal calculation" take over and students just adhoc set things to zero, hoping against all logic that I will somehow not notice this. Don't be this student. If the eigenvalues are correct, the eigenvector equations are consistent and you will be able to find nonzero eigenvectors. And don't forget, the eigenvectors must be nonzero.

7.2.2 eigenvector examples

Example 7.2.11. Let $A = \begin{bmatrix} 3 & 1 \\ 3 & 1 \end{bmatrix}$ find the e -values and e -vectors of A .

$$\det(A - \lambda I) = \det \begin{bmatrix} 3 - \lambda & 1 \\ 3 & 1 - \lambda \end{bmatrix} = (3 - \lambda)(1 - \lambda) - 3 = \lambda^2 - 4\lambda = \lambda(\lambda - 4) = 0$$

We find $\lambda_1 = 0$ and $\lambda_2 = 4$. Now find the e -vector with e -value $\lambda_1 = 0$, let $u_1 = [u, v]^T$ denote the e -vector we wish to find. Calculate,

$$(A - 0I)u_1 = \begin{bmatrix} 3 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 3u + v \\ 3u + v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Obviously the equations above are redundant and we have infinitely many solutions of the form $3u + v = 0$ which means $v = -3u$ so we can write, $u_1 = \begin{bmatrix} u \\ -3u \end{bmatrix} = u \begin{bmatrix} 1 \\ -3 \end{bmatrix}$. In applications we often make a choice to select a particular e -vector. Most modern graphing calculators can calculate e -vectors. It is customary for the e -vectors to be chosen to have length one. That is a useful choice for certain applications as we will later discuss. If you use a calculator it would likely give $u_1 = \frac{1}{\sqrt{10}} \begin{bmatrix} 1 \\ -3 \end{bmatrix}$ although the $\sqrt{10}$ would likely be approximated unless your calculator is smart.

Continuing we wish to find eigenvectors $u_2 = [u, v]^T$ such that $(A - 4I)u_2 = 0$. Notice that u, v are disposable variables in this context, I do not mean to connect the formulas from the $\lambda = 0$ case with the case considered now.

$$(A - 4I)u_1 = \begin{bmatrix} -1 & 1 \\ 3 & -3 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} -u + v \\ 3u - 3v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Again the equations are redundant and we have infinitely many solutions of the form $v = u$. Hence, $u_2 = \begin{bmatrix} u \\ u \end{bmatrix} = u \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ is an eigenvector for any $u \in \mathbb{R}$ such that $u \neq 0$.

Remark 7.2.12.

It was obvious the equations were redundant in the example above. However, we need not rely on pure intuition. The problem of calculating all the e -vectors is precisely the same as finding all the vectors in the null space of a matrix. We already have a method to do that without ambiguity. We find the rref of the matrix and the general solution falls naturally from that matrix. I don't bother with the full-blown theory for simple examples because there is no need. However, with 3×3 examples it may be advantageous to keep our earlier null space theorems in mind.

Example 7.2.13. Let $A = \begin{bmatrix} 0 & 0 & -4 \\ 2 & 4 & 2 \\ 2 & 0 & 6 \end{bmatrix}$ find the e -values and e -vectors of A .

$$\begin{aligned} 0 = \det(A - \lambda I) &= \det \begin{bmatrix} -\lambda & 0 & -4 \\ 2 & 4 - \lambda & 2 \\ 2 & 0 & 6 - \lambda \end{bmatrix} \\ &= (4 - \lambda)[- \lambda(6 - \lambda) + 8] \\ &= (4 - \lambda)[\lambda^2 - 6\lambda + 8] \\ &= -(\lambda - 4)(\lambda - 4)(\lambda - 2) \end{aligned}$$

Thus we have a repeated e-value of $\lambda_1 = \lambda_2 = 4$ and $\lambda_3 = 2$. Let's find the eigenvector $u_3 = [u, v, w]^T$ such that $(A - 2I)u_3 = 0$, we find the general solution by row reduction

$$\text{rref} \left[\begin{array}{ccc|c} -2 & 0 & -4 & 0 \\ 2 & 2 & 2 & 0 \\ 2 & 0 & 4 & 0 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & 0 & 2 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right] \Rightarrow \begin{array}{l} u + 2w = 0 \\ v - w = 0 \end{array} \Rightarrow \boxed{u_3 = w \begin{bmatrix} -2 \\ 1 \\ 1 \end{bmatrix}}$$

Next find the e-vectors with e-value 4. Let $u_1 = [u, v, w]^T$ satisfy $(A - 4I)u_1 = 0$. Calculate,

$$\text{rref} \left[\begin{array}{ccc|c} -4 & 0 & -4 & 0 \\ 2 & 0 & 2 & 0 \\ 2 & 0 & 2 & 0 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right] \Rightarrow u + w = 0$$

Notice this case has two free variables, we can use v, w as parameters in the solution,

$$u_1 = \begin{bmatrix} u \\ v \\ w \end{bmatrix} = \begin{bmatrix} -w \\ v \\ w \end{bmatrix} = v \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} + w \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \Rightarrow \boxed{u_1 = v \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \text{ and } u_2 = w \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}}$$

I have boxed two linearly independent eigenvectors u_1, u_2 . These vectors will be linearly independent for any pair of nonzero constants v, w .

You might wonder if it is always the case that repeated e-values get multiple e-vectors. In the preceding example the e-value 4 had *multiplicity* two and there were likewise two linearly independent e-vectors. The next example shows that is not the case.

Example 7.2.14. Let $A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$ find the e-values and e-vectors of A .

$$\det(A - \lambda I) = \det \begin{bmatrix} 1 - \lambda & 1 \\ 0 & 1 - \lambda \end{bmatrix} = (1 - \lambda)(1 - \lambda) = 0$$

Hence we have a repeated e-value of $\lambda_1 = 1$. Find all e-vectors for $\lambda_1 = 1$, let $u_1 = [u, v]^T$,

$$(A - I)u_1 = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow v = 0 \Rightarrow \boxed{u_1 = u \begin{bmatrix} 1 \\ 0 \end{bmatrix}}$$

We have only one e-vector for this system.

Incidentally, you might worry that we could have an e-value (in the sense of having a zero of the characteristic equation) and yet have no e-vector. Don't worry about that, we always get at least one e-vector for each distinct e-value. See Proposition 7.2.6

Example 7.2.15. Let $A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$ find the e -values and e -vectors of A .

$$\begin{aligned} 0 = \det(A - \lambda I) &= \det \begin{bmatrix} 1-\lambda & 2 & 3 \\ 4 & 5-\lambda & 6 \\ 7 & 8 & 9-\lambda \end{bmatrix} \\ &= (1-\lambda)[(5-\lambda)(9-\lambda) - 48] - 2[4(9-\lambda) - 42] + 3[32 - 7(5-\lambda)] \\ &= -\lambda^3 + 15\lambda^2 + 18\lambda \\ &= -\lambda(\lambda^2 - 15\lambda - 18) \end{aligned}$$

Therefore, using the quadratic equation to factor the ugly part,

$$\lambda_1 = 0, \quad \lambda_2 = \frac{15 + 3\sqrt{33}}{2}, \quad \lambda_3 = \frac{15 - 3\sqrt{33}}{2}$$

The e -vector for e -value zero is not too hard to calculate. Find $u_1 = [u, v]^T$ such that $(A - 0I)u_1 = 0$. This amounts to row reducing A itself:

$$\text{rref} \left[\begin{array}{ccc|c} 1 & 2 & 3 & 0 \\ 4 & 5 & 6 & 0 \\ 7 & 8 & 9 & 0 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & 0 & -1 & 0 \\ 0 & 1 & 2 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right] \Rightarrow \begin{array}{l} u - w = 0 \\ v + 2w = 0 \end{array} \Rightarrow \boxed{u_1 = w \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}}$$

The e -vectors corresponding e -values λ_2 and λ_3 are hard to calculate without numerical help. Let's discuss Texas Instrument calculator output. To my knowledge, TI-85 and higher will calculate both e -vectors and e -values. For example, my ancient TI-89, displays the following if I define our matrix $A = \text{mat2}$,

$$\text{eigVl}(\text{mat2}) = \{16.11684397, -1.11684397, 1.385788954e - 13\}$$

Calculators often need a little interpretation, the third entry is really zero in disguise. The e -vectors will be displayed in the same order, they are given from the "eigVc" command in my TI-89,

$$\text{eigVc}(\text{mat2}) = \begin{bmatrix} .2319706872 & .7858302387 & .4082482905 \\ .5253220933 & .0867513393 & -.8164965809 \\ .8186734994 & -.6123275602 & .4082482905 \end{bmatrix}$$

From this we deduce that eigenvectors for λ_1, λ_2 and λ_3 are

$$u_1 = \begin{bmatrix} .2319706872 \\ .5253220933 \\ .8186734994 \end{bmatrix} \quad u_2 = \begin{bmatrix} .7858302387 \\ .0867513393 \\ -.6123275602 \end{bmatrix} \quad u_3 = \begin{bmatrix} .4082482905 \\ -.8164965809 \\ .4082482905 \end{bmatrix}$$

Notice that $1/\sqrt{6} \approx 0.408248905$ so you can see that u_3 above is simply the $u = 1/\sqrt{6}$ case for the family of e -vectors we calculated by hand already. The calculator chooses e -vectors so that the vectors have length one.

While we're on the topic of calculators, perhaps it is worth revisiting the example where there was only one e-vector. How will the calculator respond in that case? Can we trust the calculator?

Example 7.2.16. Recall Example 7.2.14. We let $A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$ and found a repeated e-value of $\lambda_1 = 1$ and single e-vector $u_1 = u \begin{bmatrix} 1 \\ 0 \end{bmatrix}$. Hey now, it's time for technology, let $A = a$,

$$\text{eigVl}(a) = \{1, 1\} \quad \text{and} \quad \text{eigVc}(a) = \begin{bmatrix} 1. & -1. \\ 0. & 1.e - 15 \end{bmatrix}$$

Behold, the calculator has given us two alleged e-vectors. The first column is the genuine e-vector we found previously. The second column is the result of machine error. The calculator was tricked by round-off error into claiming that $[-1, 0.000000000000001]$ is a distinct e-vector for A . It is not. Moral of story? When using calculator you must first master the theory or else you'll stay mired in ignorance as prescribed by your robot masters.

Finally, I should mention that TI-calculators may or may not deal with complex e-vectors adequately. There are doubtless many web resources for calculating e-vectors/values. I would wager if you Googled it you'd find an online calculator that beats any calculator. Many of you have a laptop with wireless so there is almost certainly a way to check your answers if you just take a minute or two. I don't mind you checking your answers. If I assign it in homework then I do want you to work it out without technology. Otherwise, you could get a false confidence before the test. Technology is to supplement not replace calculation.

Remark 7.2.17.

I would also remind you that there are oodles of examples beyond these lecture notes in the homework solutions from previous year(s). If these notes do not have enough examples on some topic then you should seek additional examples elsewhere, ask me, etc... Do not suffer in silence, ask for help. Thanks.

7.3 theory for eigenvalues and eigenvectors

In this subsection we collect a number of general results on eigenvalues and eigenvectors. To begin, we prepare to argue a seemingly obvious proposition, namely that an $n \times n$ matrix will have n eigenvalues. From the three examples in the earlier section that's pretty obvious, however we should avoid proof by example in as much as possible.

Theorem 7.3.1.

Fundamental Theorem of Algebra: if $P(x)$ is an n -th order polynomial complex coefficients then the equation $P(x) = 0$ has n -solutions where some of the solutions may be repeated. Moreover, if $P(x)$ is an n -th order polynomial with real coefficients then complex solutions to $P(x) = 0$ come in conjugate pairs. It follows that any polynomial with real coefficients can be factored into a unique product of repeated real and irreducible quadratic factors.

A proof of this theorem would take us far of topic here⁹. I state it to remind you what the possibilities are for the characteristic equation. Recall that the determinant is simply a product and sum of the entries in the matrix. Notice that $A - \lambda I$ has n -copies of λ and the determinant formula never repeats the same entry twice in the same summand. It follows that solving the characteristic equation for $A \in \mathbb{R}^{n \times n}$ boils down to factoring an n -th order polynomial in λ .

Proposition 7.3.2.

If $A \in \mathbb{R}^{n \times n}$ then A has n eigenvalues, however, some may be repeated and/or complex.

Proof: follows from definition of determinant and the Fundamental Theorem of Algebra ¹⁰ \square

Notice that if $P(\lambda) = \det(A - \lambda I)$ then λ_j is an e-value of the square matrix A iff $(\lambda - \lambda_j)$ divides¹¹ the characteristic polynomial $P(\lambda)$.

Proposition 7.3.3.

The constant term in the characteristic polynomial $P(\lambda) = \det(A - \lambda I)$ is the determinant of A .

Proof: Suppose the characteristic polynomial P of A has coefficients c_i :

$$P(\lambda) = \det(A - \lambda I) = c_n \lambda^n + c_{n-1} \lambda^{n-1} + \cdots + c_1 \lambda + c_0.$$

Notice that if $\lambda = 0$ then $A - \lambda I = A$ hence

$$P(0) = \det(A) = c_n 0^n + \cdots + c_1 0 + c_0.$$

Thus $\det(A) = c_0$. \square

⁹there is a nice proof which can be given in our complex variables course

¹⁰properties of eigenvalues and the characteristic equation can be understood from studying the *minimal* and *characteristic* polynomials. We take a less sophisticated approach in this course

¹¹the term "divides" is a technical term. If $f(x)$ divides $g(x)$ then there exists $h(x)$ such that $g(x) = h(x)f(x)$. In other words, $f(x)$ is a factor of $g(x)$.

Proposition 7.3.4.

Zero is an eigenvalue of A iff A is a singular matrix.

Proof: Let $P(\lambda)$ be the characteristic polynomial of A . If zero is an eigenvalue then λ must factor the characteristic polynomial. Moreover, the factor theorem tells us that $P(0) = 0$ since $(\lambda - 0)$ factors $P(\lambda)$. Thus $c_0 = 0$ and we deduce using the previous proposition that $\det(A) = c_0 = 0$. Which shows that A is singular.

Conversely, assume A is singular then $\det(A) = 0$. Again, using the previous proposition, $\det(A) = c_0$ hence $c_0 = 0$. But, this means we can factor out a λ in $P(\lambda)$ hence $P(0) = 0$ and we find zero is an e-value of A . \square .

Proposition 7.3.5.

If $A \in \mathbb{R}^{n \times n}$ then A has n eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_n$ then $\det(A) = \lambda_1 \lambda_2 \cdots \lambda_n$.

Proof: If $A \in \mathbb{R}^{n \times n}$ then A has n eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_n$ then the characteristic polynomial factors over \mathbb{C} :

$$\det(A - \lambda I) = k(\lambda - \lambda_1)(\lambda - \lambda_2) \cdots (\lambda - \lambda_n)$$

Moreover, if you think about $A - \lambda I$ it is clear that the leading term obtains a coefficient of $(-1)^n$ hence $k = (-1)^n$. If c_0 is the constant term in the characteristic polynomial then algebra reveals that $c_0 = (-1)^n(-\lambda_1)(-\lambda_2) \cdots (-\lambda_n) = \lambda_1 \lambda_2 \cdots \lambda_n$. Therefore, using Proposition 7.3.3, $\det(A) = \lambda_1 \lambda_2 \cdots \lambda_n$. \square .

Proposition 7.3.6.

If $A \in \mathbb{R}^{n \times n}$ has e-vector v with eigenvalue λ then v is a e-vector of A^k with e-value λ^k .

Proof: let $A \in \mathbb{R}^{n \times n}$ have e-vector v with eigenvalue λ . Consider,

$$A^k v = A^{k-1} A v = A^{k-1} \lambda v = \lambda A^{k-2} A v = \lambda^2 A^{k-2} v = \cdots = \lambda^k v.$$

The \cdots is properly replaced by a formal induction argument. \square .

Proposition 7.3.7.

Let A be a upper or lower triangular matrix then the eigenvalues of A are the diagonal entries of the matrix.

Proof: follows immediately from Proposition 4.3.3 since the diagonal entries of $A - \lambda I$ are of the form $A_{ii} - \lambda$ hence the characteristic equation has the form $\det(A - \lambda I) = (A_{11} - \lambda)(A_{22} - \lambda) \cdots (A_{nn} - \lambda)$ which has solutions $\lambda = A_{ii}$ for $i = 1, 2, \dots, n$. \square

We saw how this is useful in Example 4.4.5. The LU-factorization together with the proposition above gives a computationally superior method for calculation the determinant. In addition, once you have the LU-factorization of A there are many other questions about A which are easier to answer. See your text for more on this if you are interested.

7.4 linear independence of real eigenvectors

You might have noticed that e-vectors with distinct e-values are linearly independent. This is no accident.

Proposition 7.4.1.

If $A \in \mathbb{R}^{n \times n}$ has e-vector v_1 with e-value λ_1 and e-vector v_2 with e-value λ_2 such that $\lambda_1 \neq \lambda_2$ then $\{v_1, v_2\}$ is linearly independent.

Proof: Let v_1, v_2 have e-values λ_1, λ_2 respective and assume towards a contradiction that $v_2 = kv_1$ for some nonzero constant k . Multiply by the matrix A ,

$$Av_1 = A(kv_2) \Rightarrow \lambda_1 v_1 = k\lambda_2 v_2$$

But we can replace v_1 on the l.h.s. with kv_2 hence,

$$\lambda_1 kv_2 = k\lambda_2 v_2 \Rightarrow k(\lambda_1 - \lambda_2)v_2 = 0$$

Note, $k \neq 0$ and $v_2 \neq 0$ by assumption thus the equation above indicates $\lambda_1 - \lambda_2 = 0$ therefore $\lambda_1 = \lambda_2$ which is a contradiction. Therefore there does not exist such a k and the vectors are linearly independent. \square

Proposition 7.4.2.

If $A \in \mathbb{R}^{n \times n}$ has e-vectors v_1, v_2, \dots, v_k with e-values $\lambda_1, \lambda_2, \dots, \lambda_k$ such that $\lambda_i \neq \lambda_j$ for all $i \neq j$ then $\{v_1, v_2, \dots, v_k\}$ is linearly independent.

Proof: Let e-vectors v_1, v_2, \dots, v_k have e-values $\lambda_1, \lambda_2, \dots, \lambda_k$ with respect to A and assume towards a contradiction that there is some vector v_j which is a nontrivial linear combination of the other vectors:

$$v_j = c_1 v_1 + c_2 v_2 + \dots + \widehat{c_j v_j} + \dots + c_k v_k$$

Multiply by A ,

$$Av_j = c_1 Av_1 + c_2 Av_2 + \dots + \widehat{c_j Av_j} + \dots + c_k Av_k$$

Which yields,

$$\lambda_j v_j = c_1 \lambda_1 v_1 + c_2 \lambda_2 v_2 + \dots + \widehat{c_j \lambda_j v_j} + \dots + c_k \lambda_k v_k$$

But, we can replace v_j on the l.h.s with the linear combination of the other vectors. Hence

$$\lambda_j [c_1 v_1 + c_2 v_2 + \dots + \widehat{c_j v_j} + \dots + c_k v_k] = c_1 \lambda_1 v_1 + c_2 \lambda_2 v_2 + \dots + \widehat{c_j \lambda_j v_j} + \dots + c_k \lambda_k v_k$$

Consequently,

$$c_1(\lambda_j - \lambda_1)v_1 + c_2(\lambda_j - \lambda_2)v_2 + \dots + c_j(\lambda_j - \lambda_j)v_j + \dots + c_k(\lambda_j - \lambda_k)v_k = 0$$

Since $v_i \neq 0$ and c_i are not all zero it follows at least one factor $\lambda_j - \lambda_i = 0$ for $i \neq j$ but this is a contradiction since we assumed the e-values were distinct. \square

Notice the proof of the preceding two propositions was essentially identical. I provided the $k = 2$ proof to help make the second proof more accessible.

Definition 7.4.3.

Let $A \in \mathbb{R}^{n \times n}$ then a basis $\{v_1, v_2, \dots, v_n\}$ for \mathbb{R}^n is called an **eigenbasis** if each vector in the basis is an e-vector for A . Notice we assume these are real vectors since they form a basis for \mathbb{R}^n .

Example 7.4.4. We calculated in Example 7.2.13 the e-values and e-vectors of $A = \begin{bmatrix} 0 & 0 & -4 \\ 2 & 4 & 2 \\ 2 & 0 & 6 \end{bmatrix}$ were $\lambda_1 = \lambda_2 = 4$ and $\lambda_3 = 2$ with e-vectors

$$u_1 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad u_2 = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \quad u_3 = \begin{bmatrix} -2 \\ 1 \\ 1 \end{bmatrix}$$

Linear independence of u_3 from u_1, u_2 is given from the fact the e-values of u_3 and u_1, u_2 are distinct. Then it is clear that u_1 is not a multiple of u_2 thus they are linearly independent. It follows that $\{u_1, u_2, u_3\}$ form a linearly independent set of vectors in \mathbb{R}^3 , therefore $\{u_1, u_2, u_3\}$ is an eigenbasis.

Definition 7.4.5.

Let $A \in \mathbb{R}^{n \times n}$ then we call the set of all real e-vectors with real e-value λ unioned with the zero-vector the **λ -eigenspace** and we denote this set by W_λ .

Example 7.4.6. Again using Example 7.2.13 we have two eigenspaces,

$$W_4 = \text{span}\left\{ \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \right\} \quad W_2 = \text{span}\left\{ \begin{bmatrix} -2 \\ 1 \\ 1 \end{bmatrix} \right\}$$

Proposition 7.4.7.

Eigenspaces are subspaces of \mathbb{R}^n . Moreover, $\dim(W_\lambda) \leq m$ where m is multiplicity of the λ solution in the characteristic equation.

Proof: By definition zero is in the eigenspace W_λ . Suppose $x, y \in W_\lambda$ note that $A(x + cy) = Ax + cAy = \lambda x + c\lambda y = \lambda(x + cy)$ hence $x + cy \in W_\lambda$ for all $x, y \in W_\lambda$ and $c \in \mathbb{R}$ therefore $W_\lambda \leq \mathbb{R}^n$. To prove $\dim(W_\lambda) \leq m$ we simply need to show that $\dim(W_\lambda) > m$ yields a contradiction. This can be seen from showing that if there were more than m e-vectors with e-value λ then the characteristic equation would likewise have more than m solutions of λ . The question then is why does each linearly independent e-vector give a factor in the characteristic equation? Answer this question for bonus points. \square

Definition 7.4.8.

Let A be a real square matrix with real e-value λ . The dimension of W_λ is called the **geometric multiplicity** of λ . The number of times the λ solution is repeated in the characteristic equation's solution is called the **algebraic multiplicity** of λ .

We already know from the examples we've considered thus far that there will not always be an eigenbasis for a given matrix A . In general, here are the problems we'll face:

1. we could have complex e-vectors (see Example 7.7.2)
2. we could have less e-vectors than needed for a basis (see Example 7.2.14)

We can say case 2 is caused from the geometric multiplicity being less than the algebraic multiplicity. What can we do about this? If we want to adjoin vectors to make-up for the lack of e-vectors then how should we find them in case 2?

Definition 7.4.9.

A **generalized eigenvector** of order k with eigenvalue λ with respect to a matrix $A \in \mathbb{R}^{n \times n}$ is a nonzero vector v such that

$$(A - \lambda I)^k v = 0$$

It's useful to construct generalized e-vectors from a *chain-condition* if possible.

Proposition 7.4.10.

Suppose $A \in \mathbb{R}^{n \times n}$ has e-value λ and e-vector v_1 then if $(A - \lambda I)v_2 = v_1$ has a solution then v_2 is a generalized e-vector of order 2 which is linearly independent from v_1 .

Proof: Suppose $(A - \lambda I)v_2 = v_1$ is consistent then multiply by $(A - \lambda I)$ to find $(A - \lambda I)^2 v_2 = (A - \lambda I)v_1$. However, we assumed v_1 was an e-vector hence $(A - \lambda I)v_1 = 0$ and we find v_2 is a generalized e-vector of order 2. Suppose $v_2 = kv_1$ for some nonzero k then $Av_2 = Akv_1 = k\lambda v_1 = \lambda v_2$ hence $(A - \lambda I)v_2 = 0$ but this contradicts the construction of v_2 as the solution to $(A - \lambda I)v_2 = v_1$. Consequently, v_2 is linearly independent from v_1 by virtue of its construction. \square .

Example 7.4.11. Let's return to Example 7.2.14 and look for a generalized e-vector of order 2.

Recall $A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$ and we found a repeated e-value of $\lambda_1 = 1$ and single e-vector $u_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ (fix $u = 1$ for convenience). Let's complete the chain: find $v_2 = [u, v]^T$ such that $(A - I)u_2 = u_1$,

$$\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \Rightarrow v = 1, u \text{ is free}$$

Any choice of u will do, in this case we can even set $u = 0$ to find

$$u_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Clearly, $\{u_1, u_2\}$ forms a basis of $\mathbb{R}^{2 \times 1}$. It is not an eigenbasis with respect to A , however it is what is known as a **Jordan basis** for A .

Theorem 7.4.12.

Any matrix with real eigenvalues has a Jordan basis. We can always find enough generalized e-vectors to form a basis for \mathbb{R}^n with respect to A in the case that the e-values are all real.

Proof: not here, not now. This is a hard one. \square

Proposition 7.4.13.

Let $A \in \mathbb{R}^{n \times n}$ and suppose λ is an e-value of A with e-vector v_1 then if $(A - \lambda I)v_2 = v_1$, $(A - \lambda I)v_3 = v_2, \dots, (A - \lambda I)v_k = v_{k-1}$ are all consistent then $\{v_1, v_2, \dots, v_k\}$ is a linearly independent set of vectors and v_j is a generalized vector of order j for each $j = 1, 2, \dots, k$.

Proof: worth a bonus points if you can do it. \square

Usually we can find a chain of generalized e-vectors for each e-value and that will product a Jordan basis. However, there is a trap that you will not likely get caught in for a while. It is not always possible to use a single chain for each e-value. Sometimes it takes a couple chains for a single e-value. That said, the chain condition is very nice in that it automatically insures linear independence down the chain. This is important since the solution to $(A - \lambda I)^k v = 0$ and the solution to $(A - \lambda I)v = 0$ do not automatically provide a LI set. I do not attempt to describe the general algorithm to find the Jordan basis for a given matrix, I merely wish to introduce you to the idea of the Jordan form and perhaps convince you it's interesting.

Example 7.4.14. Suppose $A = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$ it is not hard to show that $\det(A - \lambda I) = (\lambda - 1)^4 =$

0. We have a quadruple e-value $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 1$.

$$0 = (A - I)\vec{u} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \Rightarrow \vec{u} = \begin{bmatrix} s_1 \\ 0 \\ s_3 \\ 0 \end{bmatrix}$$

Any nonzero choice of s_1 or s_3 gives us an e-vector. Let's define two e-vectors which are clearly linearly independent, $\vec{u}_1 = [1, 0, 0, 0]^T$ and $\vec{u}_2 = [0, 0, 1, 0]^T$. We'll find a generalized e-vector to go with each of these. There are two length two chains to find here. In particular,

$$(A - I)\vec{u}_3 = \vec{u}_1 \Rightarrow \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ s_4 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \Rightarrow s_2 = 1, s_4 = 0, s_1, s_3 \text{ free}$$

I choose $s_1 = 0$ and $s_3 = 1$ since I want a new vector, define $\vec{u}_3 = [0, 0, 1, 0]^T$. Finally solving $(A - I)\vec{u}_4 = \vec{u}_2$ for $\vec{u}_4 = [s_1, s_2, s_3, s_4]^T$ yields conditions $s_4 = 1, s_2 = 0$ and s_1, s_3 free. I choose $\vec{u}_4 = [0, 0, 0, 1]^T$. To summarize we have four linearly independent vectors which form two chains:

$$(A - I)\vec{u}_3 = \vec{u}_1, (A - I)\vec{u}_1 = 0 \quad (A - I)\vec{u}_4 = \vec{u}_2, (A - I)\vec{u}_2 = 0$$

The matrix above was in an example of a matrix in Jordan form. When the matrix is in Jordan form then the each element of then standard basis is an e-vector or generalized e-vector.

Example 7.4.15.

$$A = \begin{bmatrix} 2 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 2 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 3 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 4 \end{bmatrix}$$

Here we have the chain $\{e_1, e_2, e_3\}$ with e-value $\lambda_1 = 2$, the chain $\{e_4, e_5, e_6, e_7\}$ with e-value $\lambda_2 = 3$ and finally a lone e-vector e_8 with e-value $\lambda_3 = 4$

7.5 diagonalization

If a matrix has n -linearly independent e-vectors then we'll find that we can perform a similarity transformation to transform the matrix into a diagonal form. Let me briefly summarize what is required for us to have n -LI e-vectors. This is the natural extension of Proposition 7.4.2 to the case of repeated e-values.

Proposition 7.5.1. *criteria for real diagonalizability*

Suppose that $A \in \mathbb{R}^{n \times n}$ has distinct eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_k \in \mathbb{R}$ such that the characteristic polynomial factors as follows:

$$P_A(\lambda) = \pm(\lambda - \lambda_1)^{m_1}(\lambda - \lambda_2)^{m_2} \cdots (\lambda - \lambda_k)^{m_k}.$$

We identify m_1, m_2, \dots, m_k are the **algebraic multiplicities** of $\lambda_1, \lambda_2, \dots, \lambda_k$ respective and $m_1 + m_2 + \cdots + m_k = n$. Furthermore, suppose we say that the j -th eigenspace $W_{\lambda_j} = \{x \in \mathbb{R} \mid Ax = \lambda_j x\}$ has $\dim(W_{\lambda_j}) = n_j$ for $j = 1, 2, \dots, k$. The values n_1, n_2, \dots, n_k are called the **geometric multiplicities** of $\lambda_1, \lambda_2, \dots, \lambda_k$ respective. With all of the language above in mind we can state that if $m_j = n_j$ for all $j = 1, 2, \dots, k$ then A is diagonalizable.

All the proposition above really says is that if there exists an eigenbasis for A then it is diagonalizable. Simply take the union of the basis for each eigenspace and note the LI of this union follows

immediately from Proposition 7.4.2 and the fact they are bases¹². Once we have an eigenbasis we still need to prove diagonalizability follows. Since that is what is most interesting I'll restate it once more. Note in the proposition below the e-values may be repeated.

Proposition 7.5.2.

Suppose that $A \in \mathbb{R}^{n \times n}$ has e-values $\lambda_1, \lambda_2, \dots, \lambda_n$ with linearly independent e-vectors v_1, v_2, \dots, v_n . If we define $V = [v_1|v_2|\dots|v_n]$ then $D = V^{-1}AV$ where D is a diagonal matrix with the eigenvalues down the diagonal: $D = [\lambda_1 e_1|\lambda_2 e_2|\dots|\lambda_n e_n]$.

Proof: Notice that V is invertible since we assume the e-vectors are linearly independent. Moreover, $V^{-1}V = I$ in terms of columns translates to $V^{-1}[v_1|v_2|\dots|v_n] = [e_1|e_2|\dots|e_n]$. From which we deduce that $V^{-1}v_j = e_j$ for all j . Also, since v_j has e-value λ_j we have $Av_j = \lambda_j v_j$. Observe,

$$\begin{aligned} V^{-1}AV &= V^{-1}A[v_1|v_2|\dots|v_n] \\ &= V^{-1}[Av_1|Av_2|\dots|Av_n] \\ &= V^{-1}[\lambda_1 v_1|\lambda_2 v_2|\dots|\lambda_n v_n] \\ &= V^{-1}[\lambda_1 v_1|\lambda_2 v_2|\dots|\lambda_n v_n] \\ &= [\lambda_1 V^{-1}v_1|\lambda_2 V^{-1}v_2|\dots|\lambda_n V^{-1}v_n] \\ &= [\lambda_1 e_1|\lambda_2 e_2|\dots|\lambda_n e_n] \quad \square. \end{aligned}$$

Remark 7.5.3.

In general, it is always possible to take a matrix with real e-values and perform a similarity transformation to a matrix in Jordan form. The similarity transformation is constructed in basically the same way as before; we calculate a Jordan basis then transform by its matrix. This is precisely what we just did in the diagonalizable case. Incidentally, a diagonal matrix is also in Jordan form but obviously the converse is not true in general. Finally, if there are complex e-values you can still perform a similarity transformation to a matrix with a complex Jordan form. To complete the story of canonical forms we should also study the rational canonical form and see how all of this ties back into the theory of polynomials and modules.

Example 7.5.4. Revisit Example 7.2.11 where we learned $A = \begin{bmatrix} 3 & 1 \\ 3 & 1 \end{bmatrix}$ had e-values $\lambda_1 = 0$ and $\lambda_2 = 4$ with e-vectors: $u_1 = [1, -3]^T$ and $u_2 = [1, 1]^T$. Let's follow the advice of the proposition above and diagonalize the matrix. We need to construct $U = [u_1|u_2]$ and calculate U^{-1} , which is easy since this is a 2×2 case:

$$U = \begin{bmatrix} 1 & 1 \\ -3 & 1 \end{bmatrix} \quad \Rightarrow \quad U^{-1} = \frac{1}{4} \begin{bmatrix} 1 & -1 \\ 3 & 1 \end{bmatrix}$$

¹²actually there is something to show here but I leave it to the reader for now

Now multiply,

$$U^{-1}AU = \frac{1}{4} \begin{bmatrix} 1 & -1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 3 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ -3 & 1 \end{bmatrix} = \frac{1}{4} \begin{bmatrix} 1 & -1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 0 & 4 \\ 0 & 4 \end{bmatrix} = \frac{1}{4} \begin{bmatrix} 0 & 0 \\ 0 & 16 \end{bmatrix}$$

Therefore, we find confirmation of the proposition, $U^{-1}AU = \begin{bmatrix} 0 & 0 \\ 0 & 4 \end{bmatrix}$.

Notice there is one very unsettling aspect of diagonalization; we need to find the inverse of a matrix. Generally this is not pleasant. Orthogonality will offer an insight to help us here. We'll develop additional tools to help with this topic in the next chapter.

Calculational inconveniences aside, we have all the tools we need to diagonalize a matrix. What then is the point? Why would we care if a matrix is diagonalized? One reason is that we can calculate arbitrary powers of the matrix with a simple calculation. Note that: if $A \sim D$ then $A^k \sim D^k$. In particular: if $D = P^{-1}AP$ then $A = PDP^{-1}$ thus:

$$A^k = \underbrace{AA \cdots A}_{k\text{-factors}} = (PDP^{-1})(PDP^{-1}) \cdots (PDP^{-1}) = PD^kP^{-1}.$$

Note, D^k is easy to calculate. Try this formula out on the last example. Try calculating A^{25} directly and then indirectly via this similarity transformation idea.

Beyond this there are applications of diagonalization too numerous to list. One reason I particularly like the text by Lay is he adds much detail on possible applications that I do not go into here. See sections 4.8, 4.9, 5.6, 5.7 for more on the applications of eigenvectors and diagonalization. My chapter 9 does go considerably beyond Lay's text on the problem of systems of ordinary differential equations so you could also look there if you thirst for applications of eigenvectors.

7.5.1 linear differential equations and e-vectors: diagonalizable case

Any system of linear differential equations with constant coefficients¹³ can be reformulated into a single system of linear differential equations in **normal form** $\frac{d\vec{x}}{dt} = A\vec{x} + \vec{f}$ where $A \in \mathbb{R}^{n \times n}$ and $\vec{f}: \mathbb{R} \rightarrow \mathbb{R}^n$ is a vector-valued function of a real variable which is usually called the **inhomogeneous term**. To begin suppose $\vec{f} = 0$ so the problem becomes the homogeneous system $\frac{d\vec{x}}{dt} = A\vec{x}$. We wish to find a vector-valued function $\vec{x}(t) = (x_1(t), x_2(t), \dots, x_n(t))$ such that when we differentiate it we obtain the same result as if we multiplied it by A . This is what it means to solve the differential equation $\frac{d\vec{x}}{dt} = A\vec{x}$. Essentially, solving this DEqn is like performing n -integrations at once. For each integration we get a constant, these constants are fixed by initial conditions if we have n of them. In any event, the general solution has the form:

$$\vec{x}(t) = c_1\vec{x}_1(t) + c_2\vec{x}_2(t) + \cdots + c_n\vec{x}_n(t)$$

¹³there are many other linear differential equations which are far more subtle than the ones we consider here, however, this case is of central importance to a myriad of applications

where $\{\vec{x}_1(t), \vec{x}_2(t), \dots, \vec{x}_n(t)\}$ is a LI set of solutions to $\frac{d\vec{x}}{dt} = A\vec{x}$ meaning $\frac{d\vec{x}_j}{dt} = A\vec{x}_j$ for each $j = 1, 2, \dots, n$. Therefore, if we can find these n -LI solutions then we've solved the problem. It turns out that the solutions are particularly simple if the matrix is diagonalizable: suppose $\{\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n\}$ is an eigenbasis with e-values $\lambda_1, \lambda_2, \dots, \lambda_n$. Let $\vec{x}_j = e^{\lambda_j t} \vec{u}_j$ and observe that

$$\frac{d\vec{x}_j}{dt} = \frac{d}{dt}[e^{\lambda_j t} \vec{u}_j] = \frac{d}{dt}[e^{\lambda_j t}] \vec{u}_j = e^{\lambda_j t} \lambda_j \vec{u}_j = e^{\lambda_j t} A \vec{u}_j = A e^{\lambda_j t} \vec{u}_j = A \vec{x}_j.$$

We find that each eigenvector \vec{u}_j yields a solution $\vec{x}_j = e^{\lambda_j t} \vec{u}_j$. If there are n -LI e-vectors then we obtain n -LI solutions.

Example 7.5.5. Consider for example, the system

$$x' = x + y, \quad y' = 3x - y$$

We can write this as the matrix problem

$$\underbrace{\begin{bmatrix} x' \\ y' \end{bmatrix}}_{d\vec{x}/dt} = \underbrace{\begin{bmatrix} 1 & 1 \\ 3 & -1 \end{bmatrix}}_A \underbrace{\begin{bmatrix} x \\ y \end{bmatrix}}_{\vec{x}}$$

It is easily calculated that A has eigenvalue $\lambda_1 = -2$ with e-vector $\vec{u}_1 = (-1, 3)$ and $\lambda_2 = 2$ with e-vectors $\vec{u}_2 = (1, 1)$. The general solution of $d\vec{x}/dt = A\vec{x}$ is thus

$$\vec{x}(t) = c_1 e^{-2t} \begin{bmatrix} -1 \\ 3 \end{bmatrix} + c_2 e^t \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -c_1 e^{-2t} + c_2 e^{2t} \\ 3c_1 e^{-2t} + c_2 e^{2t} \end{bmatrix}$$

So, the **scalar solutions** are simply $\boxed{x(t) = -c_1 e^{-2t} + c_2 e^{2t}}$ and $\boxed{y(t) = 3c_1 e^{-2t} + c_2 e^{2t}}$.

Thus far I have simply told you how to solve the system $d\vec{x}/dt = A\vec{x}$ with e-vectors, it is interesting to see what this means geometrically. For the sake of simplicity we'll continue to think about the preceding example. In it's given form the DEqn is **coupled** which means the equations for the derivatives of the dependent variables x, y cannot be solved one at a time. We have to solve both at once. In the next example I solve the same problem we just solved but this time using a change of variables approach.

Example 7.5.6. Suppose we change variables using the diagonalization idea: introduce new variables \bar{x}, \bar{y} by $P(\bar{x}, \bar{y}) = (x, y)$ where $P = [\vec{u}_1 | \vec{u}_2]$. Note $(\bar{x}, \bar{y}) = P^{-1}(x, y)$. We can diagonalize A by the similarity transformation by P ; $D = P^{-1}AP$ where $\text{Diag}(D) = (-2, 2)$. Note that $A = PDP^{-1}$ hence $d\vec{x}/dt = A\vec{x} = PDP^{-1}\vec{x}$. Multiply both sides by P^{-1} :

$$P^{-1} \frac{d\vec{x}}{dt} = P^{-1} P D P^{-1} \vec{x} \Rightarrow \frac{d(P^{-1} \vec{x})}{dt} = D(P^{-1} \vec{x}).$$

You might not recognize it but the equation above is decoupled. In particular, using the notation $(\bar{x}, \bar{y}) = P^{-1}(x, y)$ we read from the matrix equation above that

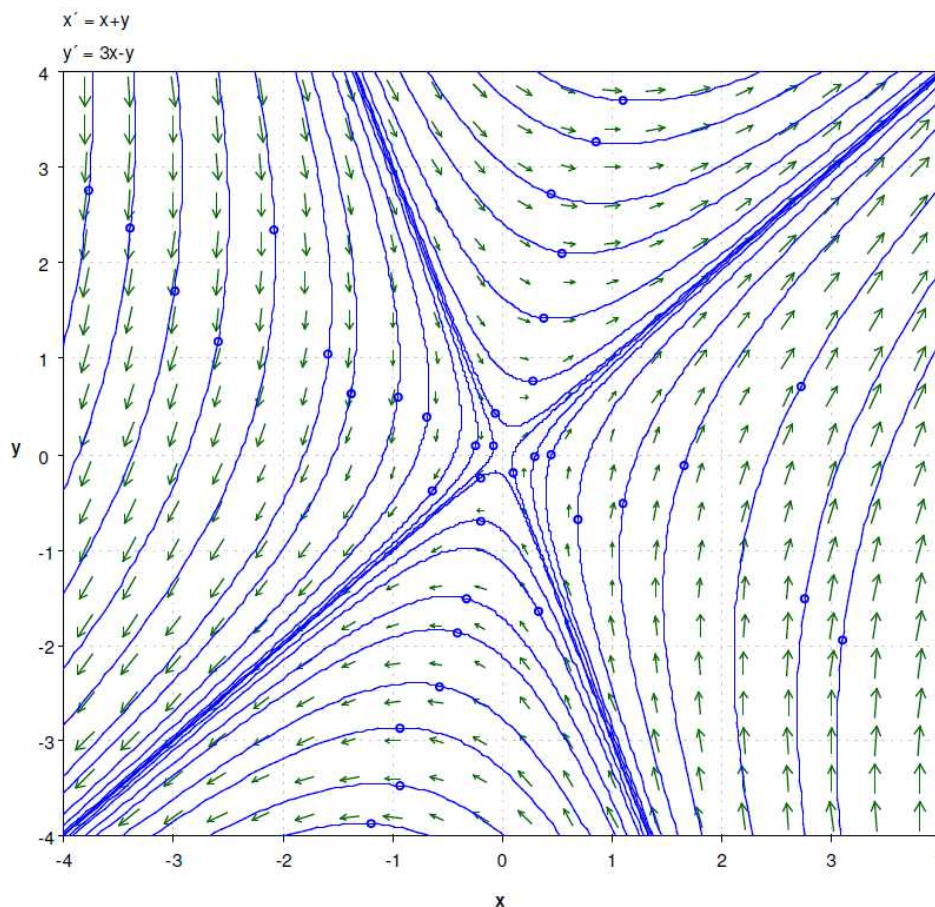
$$\frac{d\bar{x}}{dt} = -2\bar{x}, \quad \frac{d\bar{y}}{dt} = 2\bar{y}.$$

Separation of variables and a little algebra yields that $\bar{x}(t) = c_1 e^{-2t}$ and $\bar{y}(t) = c_2 e^{2t}$. Finally, to find the solution back in the original coordinate system we multiply $P^{-1}\bar{x} = (c_1 e^{-2t}, c_2 e^{2t})$ by P to isolate \vec{x} ,

$$\vec{x}(t) = \begin{bmatrix} -1 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} c_1 e^{-2t} \\ c_2 e^{2t} \end{bmatrix} = \begin{bmatrix} -c_1 e^{-2t} + c_2 e^{2t} \\ 3c_1 e^{-2t} + c_2 e^{2t} \end{bmatrix}.$$

This is the same solution we found in the last example. Usually linear algebra texts present this solution because it shows more interesting linear algebra, however, from a pragmatic viewpoint the first method is clearly faster.

Finally, we can better appreciate the solutions we found if we plot the direction field $(x', y') = (x+y, 3x-y)$ via the "pplane" tool in Matlab. I have clicked on the plot to show a few representative trajectories (solutions):



7.5.2 linear differential equations and e-vectors: non-diagonalizable case

Generally, there does not exist an eigenbasis for the matrix in $d\vec{x}/dt = A\vec{x}$. If the e-values are all real then the remaining solutions are obtained from the matrix exponential. It turns out that

$X = \exp(tA)$ is a solution matrix for $d\vec{x}/dt = A\vec{x}$ thus each column in the matrix exponential is a solution. However, direct computation of the matrix exponential is not usually tractable. Instead, an indirect approach is used. One calculates generalized e-vectors which when multiplied on $\exp(tA)$ yield very simple solutions. For example, if $(A - 3I)\vec{u}_1 = 0$ and $(A - 3I)\vec{u}_2 = \vec{u}_1$ and $(A - 3I)\vec{u}_3 = \vec{u}_2$ is a chain of generalized e-vectors with e-value $\lambda = 3$ we obtain solutions to $d\vec{x}/dt = A\vec{x}$ of the form:

$$\vec{x}_1(t) = e^{3t}\vec{u}_1, \quad \vec{x}_2(t) = e^{3t}(\vec{u}_2 + t\vec{u}_1), \quad \vec{x}_3(t) = e^{3t}(\vec{u}_3 + t\vec{u}_2 + \frac{1}{2}t^2\vec{u}_1).$$

All these formulas stem from a simplification of $\vec{x}_j = e^{tA}\vec{u}_j$ which I call the *magic formula*. That said, if you'd like to understand what in the world this subsection really means then you probably should read the DEqns chapter. There is one case left, if we have complex e-valued then A is not real-diagonalizable and the solutions actually have the form $\vec{x}(t) = \operatorname{Re}(e^{tA}\vec{u})$ or $\vec{x}(t) = \operatorname{Im}(e^{tA}\vec{u})$ where \vec{u} is either a complex e-vector or a generalized complex e-vector. Again, I leave the details for the later chapter. My point here is mostly to alert you to the fact that there are deep and interesting connections between diagonalization and the Jordan form and the solutions to corresponding differential equations.

7.6 invariants of linear transformations

Let V be a finite dimensional vector space. If $T : V \rightarrow V$ then both $\det(T)$ and $\operatorname{Tr}(T)$ are uniquely specified by calculation of the determinant and trace with respect to any particular coordinate system on V . There are a number of other interesting quantities associated with dimensions of various subspaces of the linear transformation. Typically, the corresponding subspace in \mathbb{R}^n depends on the choice of coordinate but the dimension of the subspace does not change when we perform a similarity transformation.

Example 7.6.1. Consider the matrix

$$B = \begin{bmatrix} 4 & 2 & 2 \\ 0 & 0 & -4 \\ 0 & 2 & 6 \end{bmatrix}.$$

You can calculate the characteristic polynomial for B is $P_B(\lambda) = \det(B - \lambda I) = (\lambda - 4)^2(\lambda - 2)$ thus we find e-values of $\lambda_1 = 4$ and $\lambda_2 = 2$. Its also easy to calculate two LI e-vectors for $\lambda_1 = 4$ namely $(1, 0, 0)$ and $(0, 1, -1)$ and one e-vector $(1, -2, 1)$ with e-value $\lambda_2 = 2$. The e-spaces have the form

$$W_{\lambda_1}^B = \operatorname{span}\{(1, 0, 0), (0, 1, -1)\} \quad W_{\lambda_2}^B = \operatorname{span}\{(1, -2, 1)\}$$

Clearly $\dim W_{\lambda_1}^B = 2$ and $\dim W_{\lambda_2}^B = 1$.

Perhaps these seem a bit familiar. Recall from Example 7.2.13 that the matrix

$$A = \begin{bmatrix} 0 & 0 & -4 \\ 2 & 4 & 2 \\ 2 & 0 & 6 \end{bmatrix}$$

also had e -values $\lambda_1 = 4$ and $\lambda_2 = 2$. However, the e -spaces have the form

$$W_{\lambda_1}^A = \text{span}\{(0, 1, 0), (-1, 0, 1)\} \quad W_{\lambda_2}^A = \text{span}\{(-2, 1, 1)\}$$

I constructed B by performing a similarity transformation by $P = E_{1 \leftrightarrow 2}$ so it is in fact true that $B \sim A$. Therefore, we can take the following view of this example: the matrix A defines a linear operator $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$ by $T(v) = Av$. The e -values of T are $\lambda_1 = 4$ and $\lambda_2 = 2$ and the dimensions of the corresponding e -spaces are 2 and 1 respectively. If we calculate the e -spaces $W_{\lambda_1}^B, W_{\lambda_2}^B$ for $[T]_{\beta, \beta} = B$ with respect to a nonstandard basis β then the e -spaces will not be the same subspaces of \mathbb{R}^3 as $W_{\lambda_1}^A, W_{\lambda_2}^A$.

Similar patterns will emerge if we study an abstract linear operator $T : V \rightarrow V$. We choose a basis β_1 for V then the e -spaces for $[T]_{\beta_1, \beta_1}$ will differ from those e -spaces of $[T]_{\beta_2, \beta_2}$. The e -spaces are all isomorphic to the corresponding abstract e -space which is in V . In particular, $W_\lambda = \text{span}\{v \in V \mid T(v) = \lambda v\}$ maps down to $W_\lambda^\beta = \{x \in \mathbb{R}^n \mid [T]_{\beta, \beta}x = \lambda x\}$ and the precise locations of this e -space depends on the choice of coordinates. An **invariant** is something we can calculate for a linear operator which is independent of our choice of basis. Clearly the dimensions of the e -spaces are invariants of a linear operator. In physics invariants are often something physically interesting.

Remark 7.6.2.

If $T : V \rightarrow V$ is a linear transformation then the following are invariants:

1. nullity of $T = \dim(\text{Null}([T]_{\beta, \beta}))$,
2. rank of $T = \dim(\text{Col}([T]_{\beta, \beta}))$,
3. characteristic polynomial of T is $P(\lambda) = \det([T]_{\beta, \beta} - \lambda I)$,
4. eigenvalues of T are solutions of $\det([T]_{\beta, \beta} - \lambda I) = 0$,
5. eigenspace dimension of $T = \dim(\text{Null}([T]_{\beta, \beta} - \lambda I))$,
6. $\text{trace}(T) = \text{trace}([T]_{\beta, \beta})$
7. $\det(T) = \det([T]_{\beta, \beta})$

Despite the apparent dependence on the basis β the objects above are uniquely defined. If we use a basis $\gamma \neq \beta$ in the definitions above then we will still obtain the same numbers and polynomial.

There are two interesting definitions that we could have presented in earlier chapters but I have delayed until this juncture because I wanted to give e-vector examples to illustrate the definitions. First, the concept of an invariant subspace of a linear transformation.

Definition 7.6.3.

Suppose $T : V \rightarrow V$ is a linear transformation and $V_1 \leq V$ then we say that V_1 is an **invariant subspace** of T if $T(V_1) \subseteq V_1$.

Second the concept of a direct sum decomposition of a vector space into mostly non-overlapping subspaces:

Definition 7.6.4.

Let V be a vector space and $W_1, W_2 \leq V$. If every $v \in V$ can be written as $v = w_1 + w_2$ for a some pair of $w_1 \in W_1$ and $w_2 \in W_2$ then we say that $V = W_1 + W_2$ is the **sum** of W_1 and W_2 . If $V = W_1 + W_2$ and $W_1 \cap W_2 = \{0\}$ then we say V is a **direct sum of W_1 and W_2** and denote this by writing $V = W_1 \oplus W_2$.

Think about eigenspaces. Suppose $A \in \mathbb{R}^{n \times n}$ has all real e-values. If $\lambda_j \neq \lambda_k$ then $W_{\lambda_j} \cap W_{\lambda_k} = \{0\}$. To see this, suppose otherwise. If the intersection was nontrivial then there would exist nonzero $v \in W_{\lambda_j} \cap W_{\lambda_k}$ such that $Av = \lambda_j v$ and $Av = \lambda_k v$ hence $\lambda_j v = \lambda_k v$ thus $(\lambda_j - \lambda_k)v = 0$ and since $v \neq 0$ it follows $\lambda_j = \lambda_k$ which contradicts $\lambda_j \neq \lambda_k$. Since eigenspaces are null spaces we already have that they are subspaces. Put all of this together we have the following interesting proposition:

Proposition 7.6.5.

Suppose $A \in \mathbb{R}^{n \times n}$ is diagonalizable with distinct e-values $\lambda_1, \lambda_2, \dots, \lambda_k$ then we can factor into a direct sum of e-spaces $\mathbb{R}^n = W_{\lambda_1} \oplus W_{\lambda_2} \oplus \dots \oplus W_{\lambda_k}$. Moreover, each e-space is an invariant subspace of $L_A : \mathbb{R}^n \rightarrow \mathbb{R}^n$.

7.7 complex eigenvector examples

Before I begin the material concerning complex eigenvectors I suppose I owe the reader a little background on matrices with complex number entries.

7.7.1 concerning matrices and vectors with complex entries

To begin, we denote the complex numbers by \mathbb{C} . As a two-dimensional real vector space we can decompose the complex numbers into the direct sum of the real and pure-imaginary numbers; $\mathbb{C} = \mathbb{R} \oplus i\mathbb{R}$. In other words, any complex number $z \in \mathbb{C}$ can be written as $z = a + ib$ where $a, b \in \mathbb{R}$. It is convenient to define

If $\lambda = \alpha + i\beta \in \mathbb{C}$ for $\alpha, \beta \in \mathbb{R}$ then $Re(\lambda) = \alpha$, $Im(\lambda) = \beta$

The projections onto the real or imaginary part of a complex number are actually linear transformations from \mathbb{C} to \mathbb{R} ; $Re : \mathbb{C} \rightarrow \mathbb{R}$ and $Im : \mathbb{C} \rightarrow \mathbb{R}$. Next, complex vectors are simply n -tuples of complex numbers:

$$\mathbb{C}^n = \{(z_1, z_2, \dots, z_n) \mid z_j \in \mathbb{C}\}.$$

Definitions of scalar multiplication and vector addition follow the obvious rules: if $z, w \in \mathbb{C}^n$ and $c \in \mathbb{C}$ then

$$(z + w)_j = z_j + w_j \quad (cz)_j = cz_j$$

for each $j = 1, 2, \dots, n$. The complex n -space is again naturally decomposed into the direct sum of two n -dimensional real spaces; $\mathbb{C}^n = \mathbb{R}^n \oplus i\mathbb{R}^n$. In particular, any complex n -vector can be written uniquely as the sum of real vectors are known as the real and imaginary vector components:

$$\text{If } v = a + ib \in \mathbb{C}^n \text{ for } a, b \in \mathbb{R}^n \text{ then } Re(v) = a, \quad Im(v) = b.$$

Recall $z = x + iy \in \mathbb{C}$ has complex conjugate $z^* = x - iy$. Let $v \in \mathbb{C}^n$ we define the complex conjugate of the vector v to be v^* which is the vector of complex conjugates;

$$(v^*)_j = (v_j)^*$$

for each $j = 1, 2, \dots, n$. For example, $[1 + i, 2, 3 - i]^* = [1 - i, 2, 3 + i]$. It is easy to verify the following properties for complex conjugation of numbers and vectors:

$$(v + w)^* = v^* + w^*, \quad (cv)^* = c^*v^*, \quad v^{**} = v.$$

Complex matrices $\mathbb{C}^{m \times n}$ can be added, subtracted, multiplied and scalar multiplied in precisely the same ways as real matrices in $\mathbb{R}^{m \times n}$. However, we can also identify them as $\mathbb{C}^{m \times n} = \mathbb{R}^{m \times n} \oplus i\mathbb{R}^{m \times n}$ via the real and imaginary part maps $(Re(Z))_{ij} = Re(Z_{ij})$ and $(Im(Z))_{ij} = Im(Z_{ij})$ for all i, j . There is an obvious isomorphism $\mathbb{C}^{m \times n} \cong \mathbb{R}^{2m \times 2n}$ which follows from stringing out all the real and imaginary parts. Again, complex conjugation is also defined component-wise: $((X + iY)^*)_{ij} = X_{ij} - iY_{ij}$. It's easy to verify that

$$(Z + W)^* = Z^* + W^*, \quad (cZ)^* = c^*Z^*, \quad (ZW)^* = Z^*W^*$$

for appropriately sized complex matrices Z, W and $c \in \mathbb{C}$. Conjugation gives us a natural operation to characterize the *reality* of a variable. Let $c \in \mathbb{C}$ then c is **real** iff $c^* = c$. Likewise, if $v \in \mathbb{C}^n$ then we say that v is **real** iff $v^* = v$. If $Z \in \mathbb{C}^{m \times n}$ then we say that Z is **real** iff $Z^* = Z$. In short, an object is real if all its imaginary components are zero. Finally, while there is of course much more to say we will stop here for now.

7.7.2 complex eigenvectors

Proposition 7.7.1.

If $A \in \mathbb{R}^{n \times n}$ has e-value λ and e-vector v then λ^* is likewise an e-value with e-vector v^* for A .

Proof: We assume $Av = \lambda v$ for some $\lambda \in \mathbb{C}$ and $v \in \mathbb{C}^{n \times 1}$ with $v \neq 0$. We can write $v = a + ib$ and $\lambda = \alpha + i\beta$ for some $a, b \in \mathbb{R}^n$ and $\alpha, \beta \in \mathbb{R}$. Take the complex conjugate of $Av = \lambda v$ to find $A^*v^* = \lambda^*v^*$. But, $A \in \mathbb{R}^{n \times n}$ thus $A^* = A$ and we find $Av^* = \lambda^*v^*$. Moreover, if $v = a + ib$ and $v \neq 0$ then we cannot have $a = 0$ and $b = 0$. Thus $v = a - ib \neq 0$. Therefore, v^* is an e-vector with e-value λ^* . \square

This is a useful proposition. It means that once we calculate one complex e-vectors we almost automatically get a second e-vector merely by taking the complex conjugate.

Example 7.7.2. Let $A = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$ and find the e-values and e-vectors of the matrix. Observe that $\det(A - \lambda I) = \lambda^2 + 1$ hence the eigenvalues are $\lambda = \pm i$. Find $u_1 = [u, v]^T$ such that $(A - iI)u_1 = 0$

$$0 = \begin{bmatrix} -i & 1 \\ -1 & -i \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} -iu + v \\ -u - iv \end{bmatrix} \Rightarrow \begin{matrix} -iu + v = 0 \\ -u - iv = 0 \end{matrix} \Rightarrow v = iu \Rightarrow u_1 = u \begin{bmatrix} 1 \\ i \end{bmatrix}$$

We find infinitely many complex eigenvectors, one for each nonzero complex constant u . In applications, it may be convenient to set $u = 1$ so we can write, $u_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} + i \begin{bmatrix} 0 \\ 1 \end{bmatrix}$

Let's generalize the last example.

Example 7.7.3. Let $\theta \in \mathbb{R}$ and define $A = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}$ and find the e-values and e-vectors of the matrix. Observe

$$\begin{aligned} 0 = \det(A - \lambda I) &= \det \begin{bmatrix} \cos \theta - \lambda & \sin \theta \\ -\sin \theta & \cos \theta - \lambda \end{bmatrix} \\ &= (\cos \theta - \lambda)^2 + \sin^2 \theta \\ &= \cos^2 \theta - 2\lambda \cos \theta + \lambda^2 + \sin^2 \theta \\ &= \lambda^2 - 2\lambda \cos \theta + 1 \\ &= (\lambda - \cos \theta)^2 - \cos^2 \theta + 1 \\ &= (\lambda - \cos \theta)^2 + \sin^2 \theta \end{aligned}$$

Thus $\lambda = \cos \theta \pm i \sin \theta = e^{\pm i\theta}$. Find $u_1 = [u, v]^T$ such that $(A - e^{i\theta}I)u_1 = 0$

$$0 = \begin{bmatrix} -i \sin \theta & \sin \theta \\ -\sin \theta & -i \sin \theta \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow -iu \sin \theta + v \sin \theta = 0$$

If $\sin \theta \neq 0$ then we divide by $\sin \theta$ to obtain $v = iu$ hence $u_1 = [u, iu]^T = u[1, i]^T$ which is precisely what we found in the preceding example. However, if $\sin \theta = 0$ we obtain no condition what-so-ever on the matrix. That special case is not complex. Moreover, if $\sin \theta = 0$ it follows $\cos \theta = 1$ and in fact $A = I$ in this case. The identity matrix has the repeated eigenvalue of $\lambda = 1$ and every vector in $\mathbb{R}^{2 \times 1}$ is an e -vector.

Example 7.7.4. Let $A = \begin{bmatrix} 1 & 1 & 0 \\ -1 & 1 & 0 \\ 0 & 0 & 3 \end{bmatrix}$ find the e -values and e -vectors of A .

$$\begin{aligned} 0 = \det(A - \lambda I) &= \begin{vmatrix} 1 - \lambda & 1 & 0 \\ -1 & 1 - \lambda & 0 \\ 0 & 0 & 3 - \lambda \end{vmatrix} \\ &= (3 - \lambda)[(1 - \lambda)^2 + 1] \end{aligned}$$

Hence $\lambda_1 = 3$ and $\lambda_2 = 1 \pm i$. We have a pair of complex e -values and one real e -value. Notice that for any $n \times n$ matrix we must have at least one real e -value since all odd polynomials possess at least one zero. Let's begin with the real e -value. Find $u_1 = [u, v, w]^T$ such that $(A - 3I)u_1 = 0$:

$$\text{rref} \left[\begin{array}{ccc|c} -2 & 1 & 0 & 0 \\ -1 & -2 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right] \Rightarrow \boxed{u_1 = w \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}}$$

Next find e -vector with $\lambda_2 = 1 + i$. We wish to find $u_2 = [u, v, w]^T$ such that $(A - (1 + i)I)u_2 = 0$:

$$\left[\begin{array}{ccc|c} -i & 1 & 0 & 0 \\ -1 & -i & 0 & 0 \\ 0 & 0 & -1 - i & 0 \end{array} \right] \xrightarrow[\underline{-1-i}r_3 \rightarrow r_3]{r_2 + ir_1 \rightarrow r_2} \left[\begin{array}{ccc|c} -i & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{array} \right]$$

One more row-swap and a rescaling of row 1 and it's clear that

$$\text{rref} \left[\begin{array}{ccc|c} -i & 1 & 0 & 0 \\ -1 & -i & 0 & 0 \\ 0 & 0 & -1 - i & 0 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & i & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right] \Rightarrow \begin{matrix} u + iv = 0 \\ w = 0 \end{matrix} \Rightarrow \boxed{u_2 = v \begin{bmatrix} i \\ 1 \\ 0 \end{bmatrix}}$$

I chose the free parameter to be v . Any choice of a nonzero complex constant v will yield an e -vector with e -value $\lambda_2 = 1 + i$. For future reference, it's worth noting that if we choose $v = 1$ then we find

$$u_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} + i \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

We identify that $\text{Re}(u_2) = e_2$ and $\text{Im}(u_2) = e_1$

Example 7.7.5. Let $B = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$ and let $C = \begin{bmatrix} \frac{1}{2} & \frac{\sqrt{3}}{2} \\ -\frac{\sqrt{3}}{2} & \frac{1}{2} \end{bmatrix}$. Define A to be the **block matrix**

$$A = \left[\begin{array}{c|c} B & 0 \\ \hline 0 & C \end{array} \right] = \left[\begin{array}{cc|cc} 0 & 1 & 0 & 0 \\ -1 & 0 & 0 & 0 \\ \hline 0 & 0 & \frac{1}{2} & \frac{\sqrt{3}}{2} \\ 0 & 0 & -\frac{\sqrt{3}}{2} & \frac{1}{2} \end{array} \right]$$

find the e -values and e -vectors of the matrix. Block matrices have nice properties: the blocks behave like numbers. Of course there is something to prove here, and I have yet to discuss block multiplication in these notes.

$$\det(A - \lambda I) = \det \left[\begin{array}{cc|cc} B - \lambda I & 0 & & \\ & C - \lambda I & & \\ \hline & & & \end{array} \right] = \det(B - \lambda I) \det(C - \lambda I)$$

Notice that both B and C are rotation matrices. B is the rotation matrix with $\theta = \pi/2$ whereas C is the rotation by $\theta = \pi/3$. We already know the e -values and e -vectors for each of the blocks if we ignore the other block. It would be nice if a block matrix allowed for analysis of each block one at a time. This turns out to be true, I can tell you without further calculation that we have e -values $\lambda_1 = \pm i$ and $\lambda_2 = \frac{1}{2} \pm i\frac{\sqrt{3}}{2}$ which have complex e -vectors

$$u_1 = \begin{bmatrix} 1 \\ i \\ 0 \\ 0 \end{bmatrix} = e_1 + ie_2 \quad u_2 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ i \end{bmatrix} = e_3 + ie_4$$

I invite the reader to check my results through explicit calculation. Technically, this is bad form as I have yet to prove anything about block matrices. Perhaps this example gives you a sense of why we should talk about the blocks at some point.

Finally, you might wonder are there matrices which have a repeated complex e -value. And if so are there always as many complex e -vectors as there are complex e -values? The answer: sometimes.

Take for instance $A = \left[\begin{array}{c|c} B & 0 \\ \hline 0 & B \end{array} \right]$ (where B is the same B as in the preceding example) this matrix will have a repeated e -value of $\lambda = \pm i$ and you'll be able to calculate $u_1 = e_1 \pm ie_2$ and $u_2 = e_3 \pm ie_4$ are linearly independent e -vectors for A . However, there are other matrices for which only one complex e -vector is available despite a repeat of the e -value. Bonus point if you can give me an example soon (it'll need to be at least a 4×4 matrix).

7.8 linear independence of complex eigenvectors

The complex case faces essentially the same difficulties. Complex e -vectors give us pair of linearly independent vectors with which we are welcome to form a basis. However, the complex case can also fail to provide a sufficient number of complex e -vectors to fill out a basis. In such a case we

can still look for generalized complex e-vectors. Each generalized complex e-vector will give us a pair of linearly independent real vectors which are linearly independent from the pairs already constructed from the complex e-vectors. Although many of the arguments transfer directly from previous sections there are a few features which are uniquely complex.

Proposition 7.8.1.

If $A \in \mathbb{R}^{m \times n}$ has complex e-value $\lambda = \alpha + i\beta$ such that $\beta \neq 0$ and e-vector $v = a + ib \in \mathbb{C}^{n \times 1}$ such that $a, b \in \mathbb{R}^n$ then $\lambda^* = \alpha - i\beta$ is a complex e-value with e-vector $v^* = a - ib$ and $\{v, v^*\}$ is a linearly independent set of vectors over \mathbb{C} .

Proof: Proposition 7.7.1 showed that v^* is an e-vector with e-value $\lambda^* = \alpha - i\beta$. Notice that $\lambda \neq \lambda^*$ since $\beta \neq 0$. Therefore, v and v^* are e-vectors with distinct e-values. Note that Proposition 7.4.2 is equally valid for complex e-values and e-vectors. Hence, $\{v, v^*\}$ is linearly independent since these are e-vectors with distinct e-values. \square

Proposition 7.8.2.

If $A \in \mathbb{R}^{m \times n}$ has complex e-value $\lambda = \alpha + i\beta$ such that $\beta \neq 0$ and e-vector $v = a + ib \in \mathbb{C}^{n \times 1}$ such that $a, b \in \mathbb{R}^n$ then $a \neq 0$ and $b \neq 0$.

Proof: Expand $Av = \lambda v$ into the real components,

$$\lambda v = (\alpha + i\beta)(a + ib) = \alpha a - \beta b + i(\beta a + \alpha b)$$

and

$$Av = A(a + ib) = Aa + iAb$$

Equating real and imaginary components yields two real matrix equations,

$$Aa = \alpha a - \beta b \quad \text{and} \quad Ab = \beta a + \alpha b$$

Suppose $a = 0$ towards a contradiction, note that $0 = -\beta b$ but then $b = 0$ since $\beta \neq 0$ thus $v = 0 + i0 = 0$ but this contradicts v being an e-vector. Likewise if $b = 0$ we find $\beta a = 0$ which implies $a = 0$ and again $v = 0$ which contradicts v being an e-vector. Therefore, $a, b \neq 0$. \square

Proposition 7.8.3.

If $A \in \mathbb{R}^{n \times n}$ and $\lambda = \alpha + i\beta \in \mathbb{C}$ with $\alpha, \beta \in \mathbb{R}$ and $\beta \neq 0$ is an e-value with e-vector $v = a + ib \in \mathbb{C}^{n \times 1}$ and $a, b \in \mathbb{R}^n$ then $\{a, b\}$ is a linearly independent set of real vectors.

Proof: Add and subtract the equations $v = a + ib$ and $v^* = a - ib$ to deduce

$$a = \frac{1}{2}(v + v^*) \quad \text{and} \quad b = \frac{1}{2i}(v - v^*)$$

Let $c_1, c_2 \in \mathbb{R}$ then consider,

$$\begin{aligned} c_1 a + c_2 b = 0 &\Rightarrow c_1 \left[\frac{1}{2}(v + v^*) \right] + c_2 \left[\frac{1}{2i}(v - v^*) \right] = 0 \\ &\Rightarrow [c_1 - ic_2]v + [c_1 + ic_2]v^* = 0 \end{aligned}$$

But, $\{v, v^*\}$ is linearly independent hence $c_1 - ic_2 = 0$ and $c_1 + ic_2 = 0$. Adding these equations gives $2c_1 = 0$. Subtracting yields $2ic_2 = 0$. Thus $c_1 = c_2 = 0$ and we conclude $\{a, b\}$ is linearly independent. \square

Proposition 7.8.4.

If $A \in \mathbb{R}^{m \times n}$ has complex e-value $\lambda = \alpha + i\beta$ such that $\beta \neq 0$ and chain of generalized e-vectors $v_k = a_k + ib_k \in \mathbb{C}^{n \times 1}$ of orders $k = 1, 2, \dots, m$ such that $a_k, b_k \in \mathbb{R}$ then $\{a_1, b_1, a_2, b_2, \dots, a_m, b_m\}$ is linearly independent.

Proof: will earn bonus points. It's not that this is particularly hard, I'm just tired of typing at the moment. \square

7.9 diagonalization in complex case

Given a matrix $A \in \mathbb{R}^{n \times n}$, we restrict our attention to the case that there are enough e-vectors both real and complex to complete a basis for \mathbb{R}^n . We have seen that each complex e-vector yields two LI real vectors so if we have k -complex e-vectors we assume that there are another $n - 2k$ -real e-vectors to complete a basis for \mathbb{R}^n . This is not an e-basis, but it's close. We seek to analyze how this basis will transform a given matrix. These notes loosely follow Lay's Text pages 339-341.

To begin let's try an experiment using the e-vector and complex e-vectors for found in Example 7.7.4. We'll perform a similarity transformation based on this complex basis: $\beta = \{(i, 1, 0), (-i, 1, 0), (0, 0, 1)\}$. Notice that

$$[\beta] = \begin{bmatrix} i & -i & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \Rightarrow [\beta]^{-1} = \frac{1}{2} \begin{bmatrix} -i & 1 & 0 \\ i & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

Then, we can calculate that

$$[\beta]^{-1} A [\beta] = \frac{1}{2} \begin{bmatrix} -i & 1 & 0 \\ i & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 \\ -1 & 1 & 0 \\ 0 & 0 & 3 \end{bmatrix} \begin{bmatrix} i & -i & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1+i & 0 & 0 \\ 0 & 1-i & 0 \\ 0 & 0 & 3 \end{bmatrix}$$

I would say that A is complex-diagonalizable in this case. However, usually we are interested in obtaining factorizations in terms of real matrices so we should continue thinking.

Example 7.9.1. Suppose $C = \begin{bmatrix} a & -b \\ b & a \end{bmatrix}$. We can calculate that $\det(A - \lambda I) = (a - \lambda)^2 + b^2 = 0$ hence we have two(one), typically complex, e-value $\lambda = a \pm ib$. Denoting $r = \sqrt{a^2 + b^2}$ (the modulus

of $a + ib$). We can work out that

$$C = \begin{bmatrix} a & -b \\ b & a \end{bmatrix} = r \begin{bmatrix} a/r & -b/r \\ b/r & a/r \end{bmatrix} = \begin{bmatrix} r & 0 \\ 0 & r \end{bmatrix} \begin{bmatrix} \cos(\beta) & -\sin(\beta) \\ \sin(\beta) & \cos(\beta) \end{bmatrix}$$

Therefore, a 2×2 matrix with complex-evalue will factor into a dilation by the modulus of the e-value $|\lambda|$ times a rotation by the arugment of the e-value. If we write $\lambda = r \exp(i\beta)$ then we can identify that $r > 0$ is the modulus and β is an arugment (there is degeneracy here because angle are multiply defined).

Continuing to think about the 2×2 case, note that our complex e-vector yields two real LI-vectors and hence a basis for \mathbb{R}^2 . Performing a similarity transformation by $P = [Re(\vec{u}) | Im(\vec{u})]$ will uncover the rotation hiding inside the matrix. We'll work this out in lecture for the example above.

I'll return to this discussion in the next chapter, there is more to say here.

Chapter 8

linear geometry

The concept of a geometry is very old. Philosophers in the nineteenth century failed miserably in their analysis of geometry and the physical world. They became mired in the popular misconception that mathematics must be physical. They argued that because 3 dimensional Euclidean geometry was the only geometry familiar to everyday experience it must surely follow that a geometry which differs from Euclidean geometry must be nonsensical. However, why should physical intuition factor into the argument? We understand now that geometry is a mathematical construct, not a physical one. There are many possible geometries. On the other hand, it would seem the geometry of space and time probably takes just one form. We are tempted by this misconception every time we ask "but what is this math really". That question is usually wrong-headed. A better question is "is this math logically consistent" and if so what physical systems is it known to model.

The modern view of geometry is stated in the language of manifolds, fiber bundles, algebraic geometry and perhaps even more fantastic structures. There is currently great debate as to how we should model the true intrinsic geometry of the universe. Branes, strings, quivers, noncommutative geometry, twistors, ... this list is endless. However, at the base of all these things we must begin by understanding what the geometry of a flat space entails.

Vector spaces are flat manifolds. They possess a global coordinate system once a basis is chosen. Up to this point we have only cared about algebraic conditions of linear independence and spanning. There is more structure we can assume. We can ask what is the length of a vector? Or, given two vectors we might want to know what is the angle between those vectors? Or when are two vectors orthogonal?

If we desire we can also insist that the basis consist of vectors which are *orthogonal* which means "perpendicular" in a generalized sense. A geometry is a vector space plus an idea of orthogonality and length. The concepts of orthogonality and length are encoded by an inner-product. Inner-products are symmetric, positive definite, bilinear forms, they're like a dot-product. Once we have a particular geometry in mind then we often restrict the choice of bases to only those bases which preserve the length of vectors.

The mathematics of orthogonality is exhibited by the dot-products and vectors in calculus III. However, it turns out the concept of an *inner-product* allows us to extend the idea of perpendicular to abstract vectors such as functions. This means we can even ask interesting questions such as "how close is one function to another" or "what is the closest function to a set of functions". Least-squares curve fitting is based on this geometry.

This chapter begins by defining dot-products and the norm (a.k.a. length) of a vector in \mathbb{R}^n . Then we discuss orthogonality, the Gram Schmidt algorithm, orthogonal complements and finally the application to the problem of least square analysis. The chapter concludes with a consideration of the similar, but abstract, concept of an inner product space. We look at how least squares generalizes to that context and we see how Fourier analysis naturally flows from our finite dimensional discussions of orthogonality.¹

Let me digress from linear algebra for a little while. In physics it is customary to only allow coordinates which fit the physics. In classical mechanics one often works with inertial frames which are related by a rigid motion. Certain quantities are the same in all inertial frames, notably force. This means Newton's laws have the same form in all inertial frames. The geometry of special relativity is 4 dimensional. In special relativity, one considers coordinates which preserve Einstein's three axioms. Allowed coordinates are related to other coordinates by Lorentz transformations. These Lorentz transformations include rotations and velocity boosts. These transformations are designed to make the speed of a light ray invariant in all frames. For a linear algebraist the vector space is the starting point and then coordinates are something we add on later. Physics, in contrast, tends to start with coordinates and if the author is kind he might warn you which transformations are allowed.

What coordinate transformations are allowed actually tells you what kind of physics you are dealing with. This is an interesting and nearly universal feature of modern physics. The allowed transformations form what is known to physicists as a "group" (however, strictly speaking these groups do not always have the strict structure that mathematicians insist upon for a group). In special relativity the group of interest is the Poincaré group. In quantum mechanics you use unitary groups because unitary transformations preserve probabilities. In supersymmetric physics you use the super Poincaré group because it is the group of transformations on superspace which preserves supersymmetry. In general relativity you allow general coordinate transformations which are locally Lorentzian because all coordinate systems are physical provided they respect special relativity in a certain approximation. In solid state physics there is something called the renormalization group which plays a central role in physical predictions of field-theoretic models. My point? Transformations of coordinates are important if you care about physics. We study the basic case of vector spaces in this course. If you are interested in the more sophisticated topics just ask, I can show you where to start reading.

¹we ignore analytical issues of convergence since we have only in mind a Fourier approximation, not the infinite series

8.1 Euclidean geometry of \mathbb{R}^n

The dot-product is a mapping from $\mathbb{R}^n \times \mathbb{R}^n$ to \mathbb{R} . We take in a pair of vectors and output a real number.

Definition 8.1.1.

Let $x, y \in \mathbb{R}^n$ we define $x \cdot y \in \mathbb{R}$ by

$$x \cdot y = x^T y = x_1 y_1 + x_2 y_2 + \cdots + x_n y_n$$

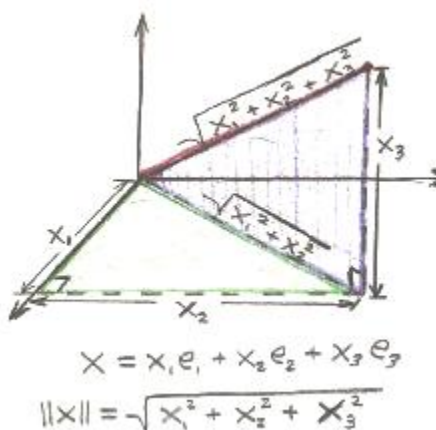
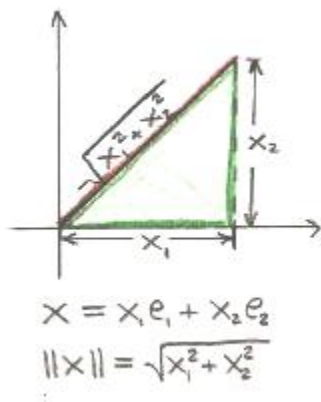
Example 8.1.2. Let $v = [1, 2, 3, 4, 5]^T$ and $w = [6, 7, 8, 9, 10]^T$

$$v \cdot w = 6 + 14 + 24 + 36 + 50 = 130$$

The dot-product can be used to define the length or norm of a vector and the angle between two vectors.

Definition 8.1.3.

The **length** or **norm** of $x \in \mathbb{R}^n$ is a real number which is defined by $\|x\| = \sqrt{x \cdot x}$. Furthermore, let x, y be nonzero vectors in \mathbb{R}^n we define the **angle** θ between x and y by $\cos^{-1} \left[\frac{x \cdot y}{\|x\| \|y\|} \right]$. \mathbb{R} together with these definitions of length and angle forms a **Euclidean Geometry**.



Technically, before we make this definition we should make sure that the formulas given above even make sense. I have not shown that $x \cdot x$ is nonnegative and how do we know that the inverse cosine is well-defined? The first proposition below shows the norm of x is well-defined and establishes several foundational properties of the dot-product.

Proposition 8.1.4.

Suppose $x, y, z \in \mathbb{R}^n$ and $c \in \mathbb{R}$ then

1. $x \cdot y = y \cdot x$
2. $x \cdot (y + z) = x \cdot y + x \cdot z$
3. $c(x \cdot y) = (cx) \cdot y = x \cdot (cy)$
4. $x \cdot x \geq 0$ and $x \cdot x = 0$ iff $x = 0$

Proof: the proof of (1.) is easy, $x \cdot y = \sum_{i=1}^n x_i y_i = \sum_{i=1}^n y_i x_i = y \cdot x$. Likewise,

$$x \cdot (y + z) = \sum_{i=1}^n x_i (y + z)_i = \sum_{i=1}^n (x_i y_i + x_i z_i) = \sum_{i=1}^n x_i y_i + \sum_{i=1}^n x_i z_i = x \cdot y + x \cdot z$$

proves (2.) and since

$$c \sum_{i=1}^n x_i y_i = \sum_{i=1}^n c x_i y_i = \sum_{i=1}^n (cx)_i y_i = \sum_{i=1}^n x_i (cy)_i$$

we find $c(x \cdot y) = (cx) \cdot y = x \cdot (cy)$. Continuing to (4.) notice that $x \cdot x = x_1^2 + x_2^2 + \cdots + x_n^2$ thus $x \cdot x$ is the sum of squares and it must be nonnegative. Suppose $x = 0$ then $x \cdot x = x^T x = 0^T 0 = 0$. Conversely, suppose $x \cdot x = 0$. Suppose $x \neq 0$ then we find a contradiction since it would have a nonzero component which implies $x_1^2 + x_2^2 + \cdots + x_n^2 \neq 0$. This completes the proof of (4.). \square

The formula $\cos^{-1} \left[\frac{x \cdot y}{\|x\| \|y\|} \right]$ is harder to justify. The inequality that we need for it to be reasonable is $\left| \frac{x \cdot y}{\|x\| \|y\|} \right| \leq 1$, otherwise we would not have a number in the $\text{dom}(\cos^{-1}) = \text{range}(\cos) = [-1, 1]$. An equivalent inequality is $|x \cdot y| \leq \|x\| \|y\|$ which is known as the **Cauchy-Schwarz** inequality.

Proposition 8.1.5.

If $x, y \in \mathbb{R}^n$ then $|x \cdot y| \leq \|x\| \|y\|$

Proof: I've looked in a few linear algebra texts and I must say the proof given in Spence, Insel and Friedberg is probably the most efficient and clear. Other texts typically run up against a quadratic inequality in some part of their proof (for example the linear algebra texts by Apostol, Larson & Edwards, Anton & Rorres to name a few). That is somehow hidden in the proof that follows: let $x, y \in \mathbb{R}^n$. If either $x = 0$ or $y = 0$ then the inequality is clearly true. Suppose then that both x and y are nonzero vectors. It follows that $\|x\|, \|y\| \neq 0$ and we can define vectors of unit-length; $\hat{x} = \frac{x}{\|x\|}$ and $\hat{y} = \frac{y}{\|y\|}$. Notice that $\hat{x} \cdot \hat{x} = \frac{x}{\|x\|} \cdot \frac{x}{\|x\|} = \frac{1}{\|x\|^2} \hat{x} \cdot x = \frac{x \cdot x}{x \cdot x} = 1$ and likewise $\hat{y} \cdot \hat{y} = 1$.

Consider,

$$\begin{aligned}
 0 &\leq \|\hat{x} \pm \hat{y}\|^2 = (\hat{x} \pm \hat{y}) \cdot (\hat{x} \pm \hat{y}) \\
 &= \hat{x} \cdot \hat{x} \pm 2(\hat{x} \cdot \hat{y}) + \hat{y} \cdot \hat{y} \\
 &= 2 \pm 2(\hat{x} \cdot \hat{y}) \\
 &\Rightarrow -2 \leq \pm 2(\hat{x} \cdot \hat{y}) \\
 &\Rightarrow \pm \hat{x} \cdot \hat{y} \leq 1 \\
 &\Rightarrow |\hat{x} \cdot \hat{y}| \leq 1
 \end{aligned}$$

Therefore, noting that $x = \|x\|\hat{x}$ and $y = \|y\|\hat{y}$,

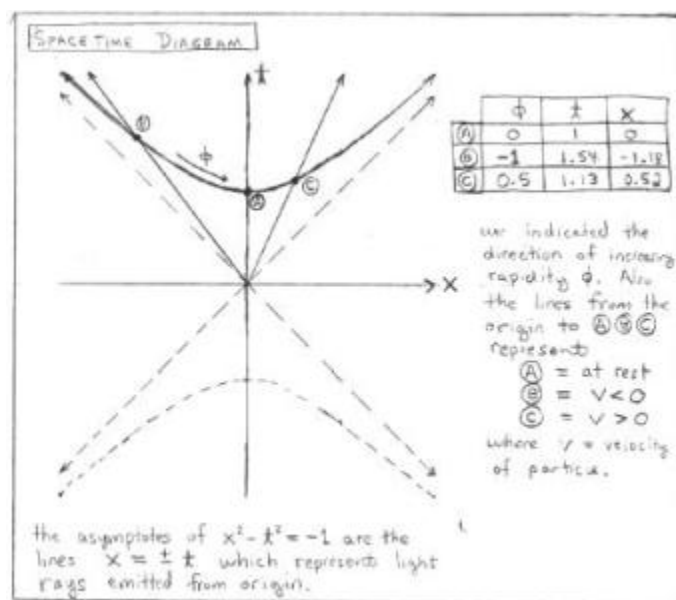
$$|x \cdot y| = \|\|x\|\hat{x} \cdot \|y\|\hat{y}\| = \|x\| \|y\| |\hat{x} \cdot \hat{y}| \leq \|x\| \|y\|.$$

The use of unit vectors is what distinguishes this proof from the others I've found. \square

Remark 8.1.6.

The dot-product is but one of many geometries for \mathbb{R}^n . We will explore generalizations of the dot-product in a later section. However, in this section we will work exclusively with the standard dot-product on \mathbb{R}^n . Generally, unless explicitly indicated otherwise, we assume Euclidean geometry for \mathbb{R}^n .

Just for fun here's a picture of a circle in the hyperbolic geometry of special relativity, technically it's not a geometry since we have nonzero-vectors with zero length (so-called null-vectors). Perhaps we will offer a course in special relativity some time and we could draw these pictures with understanding in that course.



Example 8.1.7. Let $v = [1, 2, 3, 4, 5]^T$ and $w = [6, 7, 8, 9, 10]^T$ find the angle between these vectors and calculate the unit vectors in the same directions as v and w . Recall that, $v \cdot w = 6 + 14 + 24 + 36 + 50 = 130$. Furthermore,

$$\|v\| = \sqrt{1^2 + 2^2 + 3^2 + 4^2 + 5^2} = \sqrt{1 + 4 + 9 + 16 + 25} = \sqrt{55}$$

$$\|w\| = \sqrt{6^2 + 7^2 + 8^2 + 9^2 + 10^2} = \sqrt{36 + 49 + 64 + 81 + 100} = \sqrt{330}$$

We find unit vectors via the standard trick, you just take the given vector and multiply it by the reciprocal of its length. This is called **normalizing** the vector,

$$\hat{v} = \frac{1}{\sqrt{55}}[1, 2, 3, 4, 5]^T \quad \hat{w} = \frac{1}{\sqrt{330}}[6, 7, 8, 9, 10]^T$$

The angle is calculated from the definition of angle,

$$\theta = \cos^{-1}\left(\frac{130}{\sqrt{55}\sqrt{330}}\right) = 15.21^\circ$$

It's good we have this definition, 5-dimensional protractors are very expensive.

Proposition 8.1.8.

Let $x, y \in \mathbb{R}^n$ and suppose $c \in \mathbb{R}$ then

1. $\|cx\| = |c|\|x\|$
2. $\|x + y\| \leq \|x\| + \|y\|$

Proof: let $x \in \mathbb{R}^n$ and $c \in \mathbb{R}$ then calculate,

$$\|cx\|^2 = (cx) \cdot (cx) = c^2 x \cdot x = c^2 \|x\|^2$$

Since $\|cx\| \geq 0$ the squareroot yields $\|cx\| = \sqrt{c^2}\|x\|$ and $\sqrt{c^2} = |c|$ thus $\|cx\| = |c|\|x\|$. Item (2.) is called the **triangle inequality** for reasons that will be clear when we later discuss the distance function. Let $x, y \in \mathbb{R}^n$,

$$\begin{aligned} \|x + y\|^2 &= (x + y) \cdot (x + y) && \text{defn. of norm} \\ &= |x \cdot (x + y) + y \cdot (x + y)| && \text{prop. of dot-product} \\ &= |x \cdot x + x \cdot y + y \cdot x + y \cdot y| && \text{prop. of dot-product} \\ &= | \|x\|^2 + 2x \cdot y + \|y\|^2 | && \text{prop. of dot-product} \\ &\leq \|x\|^2 + 2|x \cdot y| + \|y\|^2 && \text{triangle ineq. for } \mathbb{R} \\ &\leq \|x\|^2 + 2\|x\|\|y\| + \|y\|^2 && \text{Cauchy-Schwarz ineq.} \\ &\leq (\|x\| + \|y\|)^2 && \text{algebra} \end{aligned}$$

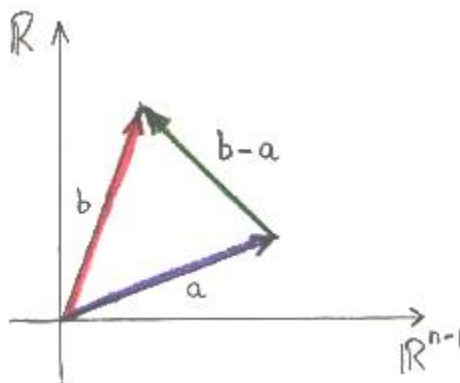
Notice that both $\|x + y\|$ and $\|x\| + \|y\|$ are nonnegative by (4.) of Proposition 8.1.4 hence the inequality above yields $\|x + y\| \leq \|x\| + \|y\|$. \square

Definition 8.1.9.

The **distance** between $a \in \mathbb{R}^n$ and $b \in \mathbb{R}^n$ is defined to be $d(a, b) \equiv \|b - a\|$.

If we draw a picture this definition is very natural. Here we are thinking of the points a, b as vectors from the origin then $b - a$ is the vector which points from a to b (this is algebraically clear since $a + (b - a) = b$). Then the distance between the points is the length of the vector that points from one point to the other. If you plug in two dimensional vectors you should recognize the distance formula from middle school math:

$$d((a_1, a_2), (b_1, b_2)) = \sqrt{(b_1 - a_1)^2 + (b_2 - a_2)^2}$$

**Proposition 8.1.10.**

Let $d : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$ be the distance function then

1. $d(x, y) = d(y, x)$
2. $d(x, y) \geq 0$
3. $d(x, x) = 0$
4. $d(x, y) + d(y, z) \geq d(x, z)$

Proof: I leave the proof of (1.), (2.) and (3.) to the reader. Item (4.) is also known as the **triangle inequality**. Think of the points x, y, z as being the vertices of a triangle, this inequality says the sum of the lengths of two sides cannot be smaller than the length of the remaining side. Let $x, y, z \in \mathbb{R}^n$ and note by the triangle inequality for $\|\cdot\|$,

$$d(x, z) = \|z - x\| = \|z - y + y - x\| \leq \|z - y\| + \|y - x\| = d(y, z) + d(x, y). \quad \square$$

We study the 2 and 3 dimensional case in some depth in calculus III. I would recommend you take that course, even if it's not "on your sheet".

8.2 orthogonality in \mathbb{R}^n

Two vectors are orthogonal if the vectors point in mutually exclusive directions. We saw in calculus III the dot-product allowed us to pick apart vectors into pieces. The same is true in n -dimensions: we can take a vector and disassemble it into component vectors which are orthogonal.

Definition 8.2.1.

Let $v, w \in \mathbb{R}^n$ then we say v and w are **orthogonal** iff $v \cdot w = 0$.

Example 8.2.2. Let $v = [1, 2, 3]^T$ describe the set of all vectors which are orthogonal to v . Let $r = [x, y, z]^T$ be an arbitrary vector and consider the orthogonality condition:

$$0 = v \cdot r = [1, 2, 3][x, y, z]^T = x + 2y + 3z = 0.$$

If you've studied 3 dimensional Cartesian geometry you should recognize this as the equation of a plane through the origin with normal vector $\langle 1, 2, 3 \rangle$.

Proposition 8.2.3. Pythagorean Theorem in n -dimensions

If $x, y \in \mathbb{R}^n$ are orthogonal vectors then $\|x\|^2 + \|y\|^2 = \|x + y\|^2$.

Proof: Calculate $\|x + y\|^2$ from the dot-product,

$$\|x + y\|^2 = (x + y) \cdot (x + y) = x \cdot x + x \cdot y + y \cdot x + y \cdot y = \|x\|^2 + \|y\|^2. \quad \square$$

Proposition 8.2.4.

The zero vector is orthogonal to all other vectors in \mathbb{R}^n .

Proof: let $x \in \mathbb{R}^n$ note $2(0) = 0$ thus $0 \cdot x = 2(0) \cdot x = 2(0 \cdot x)$ which implies $0 \cdot x = 0$. \square

Definition 8.2.5.

A set S of vectors in \mathbb{R}^n is **orthogonal** iff every pair of vectors in the set is orthogonal. If S is orthogonal and all vectors in S have length one then we say S is **orthonormal**.

Example 8.2.6. Let $u = [1, 1, 0]$, $v = [1, -1, 0]$ and $w = [0, 0, 1]$. We calculate

$$u \cdot v = 0, \quad u \cdot w, \quad v \cdot w = 0$$

thus $S = \{u, v, w\}$ is an orthogonal set. However, it is not orthonormal since $\|u\| = \sqrt{2}$. It is easy to create an orthonormal set, we just normalize the vectors; $T = \{\hat{u}, \hat{v}, \hat{w}\}$ meaning,

$$T = \left\{ \frac{1}{\sqrt{2}}[1, 1, 0], \frac{1}{\sqrt{2}}[1, -1, 0], [0, 0, 1] \right\}$$

Proposition 8.2.7. *Extended Pythagorean Theorem in n -dimensions*

If x_1, x_2, \dots, x_k are orthogonal then

$$\|x_1\|^2 + \|x_2\|^2 + \dots + \|x_k\|^2 = \|x_1 + x_2 + \dots + x_k\|^2$$

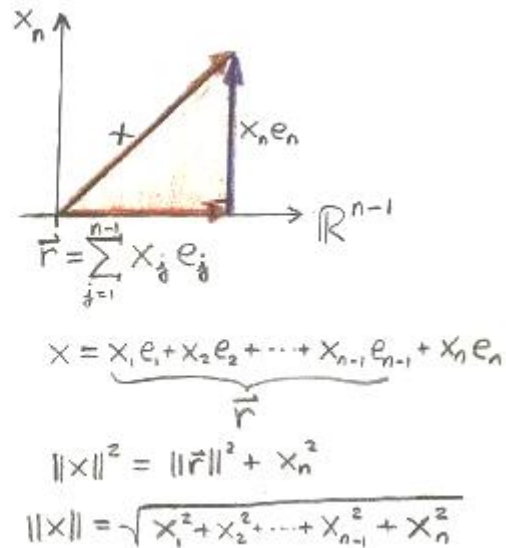
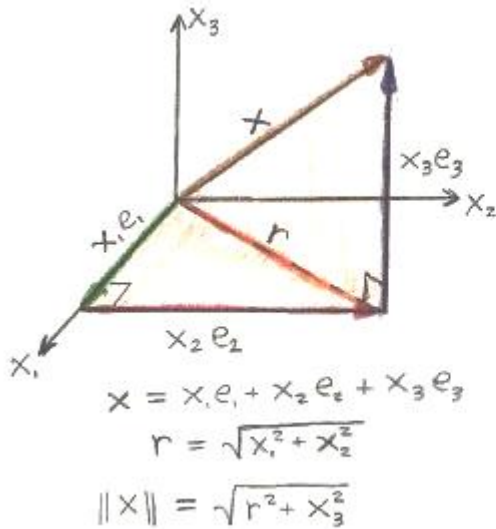
Proof: we can prove the second statement by applying the Pythagorean Theorem for two vectors repeatedly, starting with

$$\|x_1 + (x_2 + \dots + x_k)\|^2 = \|x_1\|^2 + \|x_2 + \dots + x_k\|^2$$

but then we can apply the Pythagorean Theorem to the rightmost term

$$\|x_2 + (x_3 + \dots + x_k)\|^2 = \|x_2\|^2 + \|x_3 + \dots + x_k\|^2.$$

Continuing in this fashion until we obtain the Pythagorean Theorem for k -orthogonal vectors. \square



I have illustrated the proof above in the case of three dimensions and k -dimensions, however my k -dimensional diagram takes a little imagination. Another thing to think about: given $v = v_1 e_1 + v_2 e_2 + \dots + v_n e_n$ if e_i are orthonormal then $\|v\|^2 = v_1^2 + v_2^2 + \dots + v_n^2$. Therefore, if we use a basis which is orthonormal then we obtain the standard formula for length of a vector with respect to the coordinates. If we were to use a basis of vectors which were not orthogonal or normalized then the formula for the length of a vector in terms of the coordinates could look quite different.

Example 8.2.8. Use the basis $\{v_1 = [1, 1]^T, v_2 = [2, 0]^T\}$ for $\mathbb{R}^{2 \times 1}$. Notice that $\{v_1, v_2\}$ is not orthogonal or normal. Given $x, y \in \mathbb{R}$ we wish to find $a, b \in \mathbb{R}$ such that $r = [x, y]^T = av_1 + bv_2$,

this amounts to the matrix calculation:

$$\text{rref}[v_1|v_2|r] = \text{rref} \left[\begin{array}{cc|c} 1 & 2 & x \\ 1 & 0 & y \end{array} \right] = \left[\begin{array}{cc|c} 1 & 0 & y \\ 0 & 1 & \frac{1}{2}(x-y) \end{array} \right]$$

Thus $a = y$ and $b = \frac{1}{2}(x - y)$. Let's check my answer,

$$av_1 + bv_2 = y[1, 1]^T + \frac{1}{2}(x - y)[2, 0]^T = [y + x - y, y + 0]^T = [x, y]^T.$$

Furthermore, solving for x, y in terms of a, b yields $x = 2b + a$ and $y = a$. Therefore, $\|[x, y]^T\|^2 = x^2 + y^2$ is modified to

$$\|av_1 + bv_2\|^2 = (2b + a)^2 + a^2 \neq \|av_1\|^2 + \|bv_2\|^2.$$

If we use a basis which is not orthonormal then we should take care not to assume formulas given for the standard basis equally well apply. However, if we trade the standard basis for a new basis which is orthogonal then we have less to worry about. The Pythagorean Theorem only applies in the orthogonal case. For two normalized, but possibly non-orthogonal, vectors we can replace the Pythagorean Theorem with a generalization of the Law of Cosines in \mathbb{R}^n .

$$\|av_1 + bv_2\|^2 = a^2 + b^2 + 2ab \cos \theta$$

where $v_1 \cdot v_2 = \cos \theta$. (I leave the proof to the reader)

Proposition 8.2.9.

If $S = \{v_1, v_2, \dots, v_k\} \subset \mathbb{R}^n$ is an orthogonal set of nonzero vectors then S is linearly independent.

Proof: suppose $c_1, c_2, \dots, c_k \in \mathbb{R}$ such that

$$c_1v_1 + c_2v_2 + \dots + c_kv_k = 0$$

Take the dot-product of both sides with respect to $v_j \in S$,

$$c_1v_1 \cdot v_j + c_2v_2 \cdot v_j + \dots + c_kv_k \cdot v_j = 0 \cdot v_j = 0$$

Notice all terms in the sum above vanish by orthogonality except for one term and we are left with $c_jv_j \cdot v_j = 0$. However, $v_j \neq 0$ thus $v_j \cdot v_j \neq 0$ and it follows we can divide by the nonzero scalar $v_j \cdot v_j$ leaving $c_j = 0$. But j was arbitrary hence $c_1 = c_2 = \dots = c_k = 0$ and hence S is linearly independent. \square

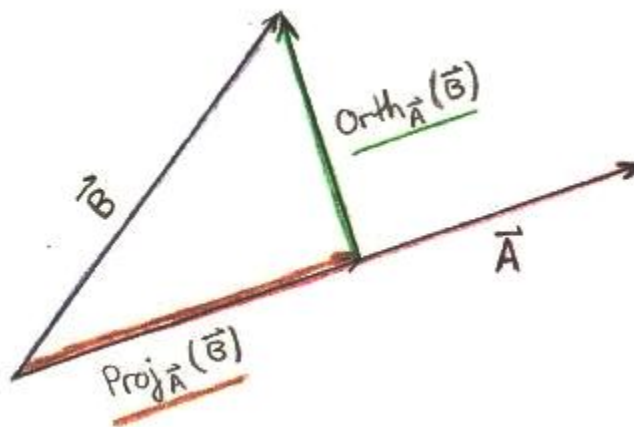
The converse of the proposition above is false. Given a linearly independent set of vectors it is not necessarily true that set is also orthogonal. However, we can modify any linearly independent set of vectors to obtain a linearly independent set. The procedure for this modification is known as the *Gram-Schmidt orthogonalization*. It is based on a generalization of the idea the vector projection from calculus III. Let me remind you: we found the projection operator to be a useful construction in calculus III. The projection operation allowed us to select the vector component of one vector that pointed in the direction of another given vector. We used this to find the distance from a point to a plane.

Definition 8.2.10.

Let $\vec{A} \neq 0, \vec{B}$ be vectors then we define

$$Proj_{\vec{A}}(\vec{B}) = (\vec{B} \cdot \hat{A})\hat{A}$$

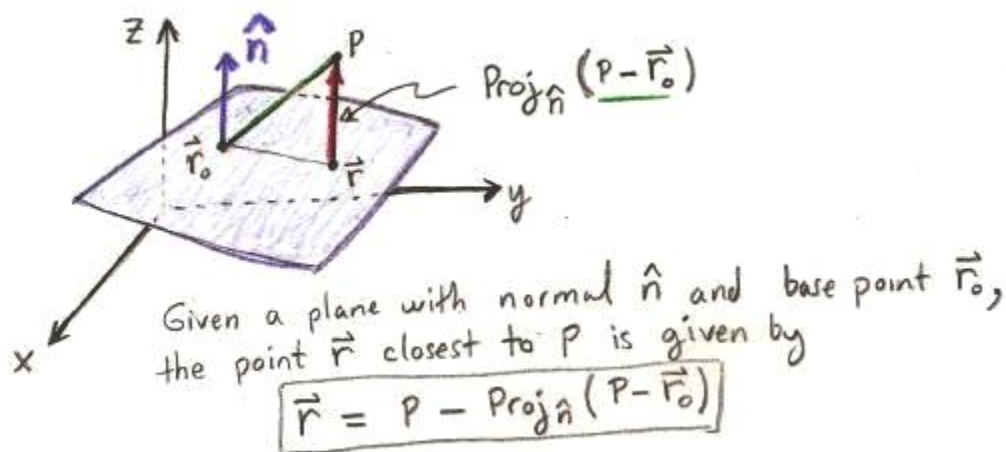
where $\hat{A} = \frac{1}{\|\vec{A}\|}\vec{A}$. Moreover, the length of $Proj_{\vec{A}}(\vec{B})$ is called the component of \vec{B} in the \vec{A} -direction and is denoted $Comp_{\vec{A}}(\vec{B}) = \|Proj_{\vec{A}}(\vec{B})\|$. Finally, the **orthogonal complement** is defined by $Orth_{\vec{A}}(\vec{B}) = \vec{B} - Proj_{\vec{A}}(\vec{B})$.



Example 8.2.11. Suppose $\vec{A} = \langle 2, 2, 1 \rangle$ and $\vec{B} = \langle 2, 4, 6 \rangle$ notice that we can also express the projection operation by $Proj_{\vec{A}}(\vec{B}) = (\vec{B} \cdot \hat{A})\hat{A} = \frac{1}{\|\vec{A}\|^2}(\vec{B} \cdot \vec{A})\vec{A}$ thus

$$Proj_{\vec{A}}(\vec{B}) = \frac{1}{9}(\langle 2, 4, 6 \rangle \cdot \langle 2, 2, 1 \rangle) \langle 2, 2, 1 \rangle = \frac{4+8+6}{9} \langle 2, 2, 1 \rangle = \langle 4, 4, 2 \rangle$$

The length of the projection vector gives $Comp_{\vec{A}}(\vec{B}) = \sqrt{16 + 16 + 4} = 6$. One application of this algebra is to calculate the distance from the plane $2x + 2y + z = 0$ to the point $(2, 4, 6)$. The "distance" from a plane to a point is defined to be the shortest distance. It's geometrically clear that the shortest path from the plane is found along the normal to the plane. If you draw a picture it's not hard to see that $(2, 4, 6) - Proj_{\vec{A}}(\vec{B}) = \langle 2, 4, 6 \rangle - \langle 4, 4, 2 \rangle = \langle -2, 0, 4 \rangle$ is the closest point to $(2, 4, 6)$ that lies on the plane $2x + 2y + z = 0$. Moreover the distance from the plane to the point is just 6.



Example 8.2.12. We studied $\vec{A} = \langle 2, 2, 1 \rangle$ and $\vec{B} = \langle 2, 4, 6 \rangle$ in the preceding example. We found that notice that $\text{Proj}_{\vec{A}}(\vec{B}) = \langle 4, 4, 2 \rangle$. The projection of \vec{B} onto \vec{A} is the part of \vec{B} which points in the direction of \vec{A} . It stands to reason that if we subtract away the projection then we will be left with the part of \vec{B} which does not point in the direction of \vec{A} , it should be orthogonal.

$$\text{Orth}_{\vec{A}}(\vec{B}) = \vec{B} - \text{Proj}_{\vec{A}}(\vec{B}) = \langle 2, 4, 6 \rangle - \langle 4, 4, 2 \rangle = \langle -2, 0, 4 \rangle$$

Let's verify $\text{Orth}_{\vec{A}}(\vec{B})$ is indeed orthogonal to \vec{A} ,

$$\text{Orth}_{\vec{A}}(\vec{B}) \cdot \vec{A} = \langle -2, 0, 4 \rangle \cdot \langle 2, 2, 1 \rangle = -4 + 4 = 0.$$

Notice that the projection operator has given us the following orthogonal decomposition of \vec{B} :

$$\langle 2, 4, 6 \rangle = \vec{B} = \text{Proj}_{\vec{A}}(\vec{B}) + \text{Orth}_{\vec{A}}(\vec{B}) = \langle 4, 4, 2 \rangle + \langle -2, 0, 4 \rangle.$$

If \vec{A}, \vec{B} are any two nonzero vectors it is probably clear that we can perform the decomposition outlined in the example above. It would not be hard to show that if $S = \{\vec{A}, \vec{B}\}$ is linearly independent then $S' = \{\vec{A}, \text{Orth}_{\vec{A}}(\vec{B})\}$ is an orthogonal set, moreover they have the same span. This is a partial answer to the converse of Proposition 8.2.9. But, what if we had three vectors instead of two? How would we orthogonalize a set of three linearly independent vectors?

Remark 8.2.13.

I hope you can forgive me for reverting to calculus III notation in the last page or two. It should be clear enough to the reader that the orthogonalization and projection operations can be implemented on either rows or columns. I return to our usual custom of thinking primarily about column vectors at this point. We've already seen the definition from Calculus III, now we turn to the n -dimensional case in matrix notation.

Definition 8.2.14.

Suppose $a \neq 0 \in \mathbb{R}^n$, define the **projection of b onto a** to be the mapping $Proj_a : \mathbb{R}^n \rightarrow \mathbb{R}^n$ such that $Proj_a(b) = \frac{1}{a^T a}(a^T b)a$. Moreover, we define $Orth_a : \mathbb{R}^n \rightarrow \mathbb{R}^n$ by $Orth_a(b) = b - Proj_a(b) = b - \frac{1}{a^T a}(a^T b)a$ for all $b \in \mathbb{R}^n$.

Proposition 8.2.15.

If $a \neq 0 \in \mathbb{R}^n$ then $Proj_a$ and $Orth_a$ are linear transformations.

1. $Orth_a(b) \cdot a = 0$ for all $b \in \mathbb{R}^n$,
2. $Orth_a(b) \cdot Proj_a(y) = 0$ for all $b, y \in \mathbb{R}^n$,
3. the projection is idempotent; $Proj_a \circ Proj_a = Proj_a$.

I leave the proof of linearity as an exercise. Begin with (1.): let $a \neq 0 \in \mathbb{R}^n$ and let $b \in \mathbb{R}^n$,

$$\begin{aligned} a \cdot Orth_a(b) &= a^T(b - \frac{1}{a^T a}(a^T b)a) \\ &= a^T b - a^T(\frac{1}{a^T a}(a^T b)a) \\ &= a^T b - \frac{1}{a^T a}(a^T b)a^T a \\ &= a^T b - a^T b = 0. \end{aligned}$$

notice I used the fact that $a^T b, a^T a$ were scalars to commute the a^T to the end of the expression. Notice that (2.) follows since $Proj_a(y) = ka$ for some constant k . Next, let $b \in \mathbb{R}^n$ and consider:

$$\begin{aligned} (Proj_a \circ Proj_a)(b) &= Proj_a(Proj_a(b)) \\ &= Proj_a(\frac{1}{a^T a}(a^T b)a) \\ &= \frac{1}{a^T a}(a^T[\frac{1}{a^T a}(a^T b)a])a \\ &= \frac{1}{a^T a}(\frac{a^T b}{a^T a}a^T a)a \\ &= \frac{1}{a^T a}(a^T b)a \\ &= Proj_a(b) \end{aligned}$$

since the above holds for all $b \in \mathbb{R}^n$ we find $Proj_a \circ Proj_a = Proj_a$. This can also be denoted $Proj_a^2 = Proj_a$. \square

Proposition 8.2.16.

If $S = \{a, b, c\}$ be a linearly independent set of vectors in \mathbb{R}^n then $S' = \{a', b', c'\}$ is an orthogonal set of vectors in \mathbb{R}^n if we define a', b', c' as follows:

$$a' = a, \quad b' = Orth_{a'}(b), \quad c' = Orth_{a'}(Orth_{b'}(c)).$$

Proof: to prove S' orthogonal we must show that $a' \cdot b' = 0$, $a' \cdot c' = 0$ and $b' \cdot c' = 0$. We already proved $a' \cdot b' = 0$ in the Proposition 8.2.15. Likewise, $a' \cdot c' = 0$ since $Orth_{a'}(x)$ is orthogonal to a' for any x . Consider:

$$\begin{aligned} b' \cdot c' &= b' \cdot Orth_{a'}(Orth_{b'}(c)) \\ &= b' \cdot [Orth_{b'}(c) - Proj_{a'}(Orth_{b'}(c))] \\ &= b' \cdot Orth_{b'}(c) - Orth_a(b) \cdot Proj_a(Orth_{b'}(c)) \\ &= 0 \end{aligned}$$

Where we again used (1.) and (2.) of Proposition 8.2.15 in the critical last step. The logic of the formulas is very natural. To construct b' we simply remove the part of b which points in the direction of a' . Then to construct c' we first remove the part of c in the b' direction and then the part in the a' direction. This means no part of c' will point in the a' or b' directions. In principle, one might worry we would subtract away so much that nothing is left, but the linear independence of the vectors insures that is not possible. If it were that would imply a linear dependence of the original set of vectors. \square

For convenience let me work out the formulas we just discovered in terms of an explicit formula with dot-products. We can also perform the same process for a set of 4 or 5 or more vectors. I'll state the process for arbitrary order, you'll forgive me if I skip the proof this time. There is a careful proof on page 379 of Spence, Insel and Friedberg. The connection between my *Orth* operator approach and the formulas in the proposition that follows is *just algebra*:

$$\begin{aligned} v'_3 &= Orth_{v'_1}(Orth_{v'_2}(v_3)) \\ &= Orth_{v'_2}(v_3) - Proj_{v'_1}(Orth_{v'_2}(v_3)) \\ &= v_3 - Proj_{v'_2}(v_3) - Proj_{v'_1}(v_3 - Proj_{v'_2}(v_3)) \\ &= v_3 - Proj_{v'_2}(v_3) - Proj_{v'_1}(v_3) - Proj_{v'_1}(Proj_{v'_2}(v_3)) \\ &= v_3 - \frac{v_3 \cdot v'_2}{v'_2 \cdot v'_2} v'_2 - \frac{v_3 \cdot v'_1}{v'_1 \cdot v'_1} v'_1 \end{aligned}$$

The last term vanished because $v'_1 \cdot v'_2 = 0$ and the projections are just scalar multiples of those vectors.

Proposition 8.2.17. The Gram-Schmidt Process

If $S = \{v_1, v_2, \dots, v_k\}$ is a linearly independent set of vectors in \mathbb{R}^n then $S' = \{v'_1, v'_2, \dots, v'_k\}$ is an orthogonal set of vectors in \mathbb{R}^n if we define v'_i as follows:

$$\begin{aligned} v'_1 &= v_1 \\ v'_2 &= v_2 - \frac{v_2 \cdot v'_1}{v'_1 \cdot v'_1} v'_1 \\ v'_3 &= v_3 - \frac{v_3 \cdot v'_2}{v'_2 \cdot v'_2} v'_2 - \frac{v_3 \cdot v'_1}{v'_1 \cdot v'_1} v'_1 \\ v'_k &= v_k - \frac{v_k \cdot v'_{k-1}}{v'_{k-1} \cdot v'_{k-1}} v'_{k-1} - \frac{v_k \cdot v'_{k-2}}{v'_{k-2} \cdot v'_{k-2}} v'_{k-2} - \dots - \frac{v_k \cdot v'_1}{v'_1 \cdot v'_1} v'_1. \end{aligned}$$

Example 8.2.18. Suppose $v_1 = [1, 0, 0, 0]^T$, $v_2 = [3, 1, 0, 0]^T$, $v_3 = [3, 2, 0, 3]^T$. Let's use the Gram-Schmidt Process to orthogonalize these vectors: let $v'_1 = v_1 = [1, 0, 0, 0]^T$ and calculate:

$$v'_2 = v_2 - \frac{v_2 \cdot v'_1}{v'_1 \cdot v'_1} v'_1 = [3, 1, 0, 0]^T - 3[1, 0, 0, 0]^T = [0, 1, 0, 0]^T.$$

Next,

$$v'_3 = v_3 - \frac{v_3 \cdot v'_2}{v'_2 \cdot v'_2} v'_2 - \frac{v_3 \cdot v'_1}{v'_1 \cdot v'_1} v'_1 = [3, 2, 0, 3]^T - 2[0, 1, 0, 0]^T - 3[1, 0, 0, 0]^T = [0, 0, 0, 3]^T$$

We find the orthogonal set of vectors $\{e_1, e_2, e_4\}$. It just so happens this is also an orthonormal set of vectors.

Proposition 8.2.19. Normalization

If $S' = \{v'_1, v'_2, \dots, v'_k\}$ is an orthogonal subset of \mathbb{R}^n then $S'' = \{v''_1, v''_2, \dots, v''_k\}$ is an orthonormal set if we define $v''_i = \widehat{v'_i} = \frac{1}{\|v'_i\|} v'_i$ for each $i = 1, 2, \dots, k$.

Example 8.2.20. Suppose $v_1 = [1, 1, 1]^T$, $v_2 = [1, 2, 3]^T$, $v_3 = [0, 0, 3]^T$ find an orthonormal set of vectors that spans $\text{span}\{v_1, v_2, v_3\}$. We can use Gram-Schmidt followed by a normalization, let $v'_1 = [1, 1, 1]^T$ then calculate

$$v'_2 = [1, 2, 3]^T - \left(\frac{1+2+3}{3}\right)[1, 1, 1]^T = [1, 2, 3]^T - [2, 2, 2]^T = [-1, 0, 1]^T.$$

as a quick check on my arithmetic note $v'_1 \cdot v'_2 = 0$ (good). Next,

$$v'_3 = [0, 0, 3]^T - \left(\frac{0(-1) + 0(0) + 3(1)}{2}\right)[-1, 0, 1]^T - \left(\frac{0(1) + 0(1) + 3(1)}{3}\right)[1, 1, 1]^T$$

$$\Rightarrow v'_3 = [0, 0, 3]^T + [\frac{3}{2}, 0, -\frac{3}{2}]^T - [1, 1, 1]^T = [\frac{1}{2}, -1, \frac{1}{2}]^T$$

again it's good to check that $v'_2 \cdot v'_3 = 0$ and $v'_1 \cdot v'_3 = 0$ as we desire. Finally, note that $\|v'_1\| = \sqrt{3}$, $\|v'_2\| = \sqrt{2}$ and $\|v'_3\| = \sqrt{3/2}$ hence

$$v''_1 = \frac{1}{\sqrt{3}}[1, 1, 1]^T, \quad v''_2 = \frac{1}{\sqrt{2}}[-1, 0, 1]^T, \quad v''_3 = \sqrt{\frac{2}{3}}[\frac{1}{2}, -1, \frac{1}{2}]^T$$

are orthonormal vectors.

Definition 8.2.21.

A basis for a subspace W of \mathbb{R}^n is an **orthogonal** basis for W iff it is an orthogonal set of vectors which is a basis for W . Likewise, an **orthonormal** basis for W is a basis which is **orthonormal**.

Proposition 8.2.22. Existence of Orthonormal Basis

If $W \leq \mathbb{R}^n$ then there exists an orthonormal basis of W

Proof: since W is a subspace it has a basis. Apply Gram-Schmidt to that basis then normalize the vectors to obtain an orthonormal basis. \square

Example 8.2.23. Let $W = \text{span}\{[1, 0, 0, 0]^T, [3, 1, 0, 0]^T, [3, 2, 0, 3]^T\}$. Find an orthonormal basis for $W \leq \mathbb{R}^{4 \times 1}$. Recall from Example 8.2.18 we applied Gram-Schmidt and found the orthonormal set of vectors $\{e_1, e_2, e_4\}$. That is an orthonormal basis for W .

Example 8.2.24. In Example 8.2.20 we found $\{v''_1, v''_2, v''_3\}$ is an orthonormal set of vectors. Since orthogonality implies linear independence it follows that this set is in fact a basis for $\mathbb{R}^{3 \times 1}$. It is an **orthonormal basis**. Of course there are other bases which are orthogonal. For example, the standard basis is orthonormal.

Example 8.2.25. Let us define $S = \{v_1, v_2, v_3, v_4\} \subset \mathbb{R}^{4 \times 1}$ as follows:

$$v_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}, \quad v_2 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}, \quad v_3 = \begin{bmatrix} 0 \\ 0 \\ 2 \\ 3 \end{bmatrix}, \quad v_4 = \begin{bmatrix} 3 \\ 2 \\ 0 \\ 3 \end{bmatrix}$$

It is easy to verify that S defined below is a linearly independent set vectors basis for $\text{span}(S) \leq \mathbb{R}^{4 \times 1}$. Let's see how to find an orthonormal basis for $\text{span}(S)$. The procedure is simple: apply the

Gram-Schmidt algorithm then normalize the vectors.

$$v'_1 = v_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}$$

$$v'_2 = v_2 - \left(\frac{v_2 \cdot v'_1}{v'_1 \cdot v'_1} \right) v'_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} - \frac{3}{3} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

$$v'_3 = v_3 - \left(\frac{v_3 \cdot v'_2}{v'_2 \cdot v'_2} \right) v'_2 - \left(\frac{v_3 \cdot v'_1}{v'_1 \cdot v'_1} \right) v'_1 = \begin{bmatrix} 0 \\ 0 \\ 2 \\ 3 \end{bmatrix} - \frac{0}{1} \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} - \frac{5}{3} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} -5 \\ 0 \\ 1 \\ 4 \end{bmatrix}$$

$$v'_4 = v_4 - \left(\frac{v_4 \cdot v'_3}{v'_3 \cdot v'_3} \right) v'_3 - \left(\frac{v_4 \cdot v'_2}{v'_2 \cdot v'_2} \right) v'_2 - \left(\frac{v_4 \cdot v'_1}{v'_1 \cdot v'_1} \right) v'_1 = \begin{bmatrix} 3 \\ 2 \\ 0 \\ 3 \end{bmatrix} - \frac{1}{14} \begin{bmatrix} -5 \\ 0 \\ 1 \\ 4 \end{bmatrix} - \begin{bmatrix} 0 \\ 2 \\ 0 \\ 0 \end{bmatrix} - \begin{bmatrix} 2 \\ 0 \\ 2 \\ 2 \end{bmatrix} = \frac{1}{14} \begin{bmatrix} 9 \\ 0 \\ -27 \\ 18 \end{bmatrix}$$

Then normalize to obtain the orthonormal basis for $\text{Span}(S)$ below:

$$\beta = \left\{ \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \frac{1}{\sqrt{42}} \begin{bmatrix} -5 \\ 0 \\ 1 \\ 4 \end{bmatrix}, \frac{1}{9\sqrt{14}} \begin{bmatrix} 9 \\ 0 \\ -27 \\ 18 \end{bmatrix} \right\}$$

Proposition 8.2.26. Coordinates with respect to an Orthonormal Basis

If $W \leq \mathbb{R}^n$ has an orthonormal basis $\{v_1, v_2, \dots, v_k\}$ and if $w = \sum_{i=1}^k w_i v_i$ then $w_i = w \cdot v_i$ for all $i = 1, 2, \dots, k$. In other words, each vector $w \in W$ may be expressed as

$$w = (w \cdot v_1)v_1 + (w \cdot v_2)v_2 + \dots + (w \cdot v_k)v_k$$

Proof: Let $w = w_1 v_1 + w_2 v_2 + \dots + w_k v_k$ and take the dot-product with v_j ,

$$w \cdot v_j = (w_1 v_1 + w_2 v_2 + \dots + w_k v_k) \cdot v_j = w_1 (v_1 \cdot v_j) + w_2 (v_2 \cdot v_j) + \dots + w_k (v_k \cdot v_j)$$

Orthonormality of the basis is compactly expressed by the Kronecker Delta; $v_i \cdot v_j = \delta_{ij}$ this is zero if $i \neq j$ and it is 1 if they are equal. The whole sum collapses except for the j -th term which yields: $w \cdot v_j = w_j$. But, j was arbitrary hence the proposition follows. \square .

The proposition above reveals the real reason we like to work with orthonormal coordinates. It's easy to figure out the coordinates, we simply take dot-products. This technique was employed with great success in (you guessed it) Calculus III. The standard $\{\hat{i}, \hat{j}, \hat{k}\}$ is an orthonormal basis and one of the first things we discuss is that if $\vec{v} = \langle A, B, C \rangle$ then $A = \vec{v} \cdot \hat{i}$, $B = \vec{v} \cdot \hat{j}$ and $C = \vec{v} \cdot \hat{k}$.

Example 8.2.27. *For the record, the standard basis of \mathbb{R}^n is an orthonormal basis and*

$$v = (v \cdot e_1)e_1 + (v \cdot e_2)e_2 + \cdots + (v \cdot e_n)e_n$$

for any vector v in \mathbb{R}^n .

Example 8.2.28. *Let $v = [1, 2, 3, 4]$. Find the coordinates of v with respect to the orthonormal basis β found in Example 8.2.25.*

$$\beta = \{f_1, f_2, f_3, f_4\} = \left\{ \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \frac{1}{\sqrt{42}} \begin{bmatrix} -5 \\ 0 \\ 1 \\ 4 \end{bmatrix}, \frac{1}{9\sqrt{14}} \begin{bmatrix} 9 \\ 0 \\ -27 \\ 18 \end{bmatrix} \right\}$$

Let us denote the coordinates vector $[v]_\beta = [w_1, w_2, w_3, w_4]$ we know we can calculate these by taking the dot-products with the vectors in the orthonormal basis β :

$$w_1 = v \cdot f_1 = \frac{1}{\sqrt{3}}[1, 2, 3, 4][1, 0, 1, 1]^T = \frac{8}{\sqrt{3}}$$

$$w_2 = v \cdot f_2 = [1, 2, 3, 4][0, 1, 0, 0]^T = 2$$

$$w_3 = v \cdot f_3 = \frac{1}{\sqrt{42}}[1, 2, 3, 4][-5, 0, 1, 4]^T = \frac{14}{\sqrt{42}}$$

$$w_4 = v \cdot f_4 = \frac{1}{9\sqrt{14}}[1, 2, 3, 4][9, 0, -27, 18]^T = \frac{0}{9\sqrt{14}} = 0$$

Therefore, $[v]_\beta = [\frac{8}{\sqrt{3}}, 2, \frac{14}{\sqrt{42}}, 0]$. Now, let's check our answer. What should this mean if it is

correct? We should be able verify $v = w_1f_1 + w_2f_2 + w_3f_3 + w_4f_4$:

$$\begin{aligned}
 w_1f_1 + w_2f_2 + w_3f_3 + w_4f_4 &= \frac{8}{\sqrt{3}} \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} + \frac{14}{\sqrt{42}} \frac{1}{\sqrt{42}} \begin{bmatrix} -5 \\ 0 \\ 1 \\ 4 \end{bmatrix} \\
 &= \frac{8}{3} \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix} + 2 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} + \frac{1}{3} \begin{bmatrix} -5 \\ 0 \\ 1 \\ 4 \end{bmatrix} \\
 &= \begin{bmatrix} 8/3 - 5/3 \\ 2 \\ 8/3 + 1/3 \\ 8/3 + 4/3 \end{bmatrix} \\
 &= \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}
 \end{aligned}$$

Well, that's a relief.

8.3 orthogonal complements and projections

Upto now we have discussed projections with respect to one vector at a time, however we can just as well discuss the projection onto some subspace of \mathbb{R}^n . We need a few definitions to clarify and motivate the projection.

Definition 8.3.1.

Suppose $W_1, W_2 \subseteq \mathbb{R}^n$ then we say W_1 is **orthogonal** to W_2 iff $w_1 \cdot w_2 = 0$ for all $w_1 \in W_1$ and $w_2 \in W_2$. We denote orthogonality by writing $W_1 \perp W_2$.

Example 8.3.2. Let $W_1 = \text{span}\{e_1, e_2\}$ and $W_2 = \text{span}\{e_3\}$ then $W_1, W_2 \leq \mathbb{R}^n$. Let $w_1 = ae_1 + be_2 \in W_1$ and $w_2 = ce_3 \in W_2$ calculate,

$$w_1 \cdot w_2 = (ae_1 + be_2) \cdot (ce_3) = ace_1 \cdot e_3 + bce_2 \cdot e_3 = 0$$

Hence $W_1 \perp W_2$. Geometrically, we have shown the xy -plane is orthogonal to the z -axis.

We notice that orthogonality relative to the basis will naturally extend to the span of the basis since the dot-product has nice linearity properties.

Proposition 8.3.3.

Suppose $W_1, W_2 \leq \mathbb{R}^n$ the subspace W_1 is **orthogonal** to the subspace W_2 iff $w_i \cdot v_j = 0$ for all i, j relative to a pair of bases $\{w_i\}$ for W_1 and $\{v_j\}$ for W_2 .

Proof: Suppose $\{w_i\}_{i=1}^r$ is a basis for $W_1 \leq \mathbb{R}^n$ and $\{v_j\}_{j=1}^s$ for $W_2 \leq \mathbb{R}^n$. If $W_1 \perp W_2$ then clearly $\{w_i\}_{i=1}^r$ is orthogonal to $\{v_j\}_{j=1}^s$. Conversely, suppose $\{w_i\}_{i=1}^r$ is orthogonal to $\{v_j\}_{j=1}^s$ then let $x \in W_1$ and $y \in W_2$:

$$x \cdot y = \left(\sum_{i=1}^r x_i w_i \right) \cdot \left(\sum_{j=1}^s y_j v_j \right) = \sum_{i=1}^r \sum_{j=1}^s x_i y_j (w_i \cdot v_j) = 0. \quad \square$$

Given a subspace W which lives in \mathbb{R}^n we might wonder what is the largest subspace which is orthogonal to W ? In $\mathbb{R}^{3 \times 1}$ it is clear that the xy -plane is the largest subspace which is orthogonal to the z -axis, however, if the xy -plane was viewed as a subset of $\mathbb{R}^{4 \times 1}$ we could actually find a volume which was orthogonal to the z -axis (in particular $\text{span}\{e_1, e_2, e_4\} \perp \text{span}\{e_3\}$).

Definition 8.3.4.

Let $W \subseteq \mathbb{R}^n$ then W^\perp is defined as follows:

$$W^\perp = \{v \in \mathbb{R}^n | v \cdot w = 0 \text{ for all } w \in W\}$$

It is clear that W^\perp is the largest subset in \mathbb{R}^n which is orthogonal to W . Better than just that, it's the largest subspace orthogonal to W .

Proposition 8.3.5.

Let $S \subset \mathbb{R}^n$ then $S^\perp \leq \mathbb{R}^n$.

Proof: Let $x, y \in S^\perp$ and let $c \in \mathbb{R}$. Furthermore, suppose $s \in S$ and note

$$(x + cy) \cdot s = x \cdot s + c(y \cdot s) = 0 + c(0) = 0.$$

Thus an arbitrary linear combination of elements of S^\perp are again in S^\perp which is nonempty as $0 \in S^\perp$ hence by the subspace test $S^\perp \leq \mathbb{R}^n$. It is interesting that S need not be a subspace for this argument to hold. \square

Example 8.3.6. Find the orthogonal complement to $W = \text{span}\{v_1 = [1, 1, 0, 0]^T, v_2 = [0, 1, 0, 2]^T\}$. Let's treat this as a matrix problem. We wish to describe a typical vector in W^\perp . Towards that goal, let $r = [x, y, z, w]^T \in W^\perp$ then the conditions that r must satisfy are $v_1 \cdot r = v_1^T r = 0$ and $v_2 \cdot r = v_2^T r = 0$. But this is equivalent to the single matrix equation below:

$$\begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow r = \begin{bmatrix} 2w \\ -2w \\ z \\ w \end{bmatrix} = z \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} + w \begin{bmatrix} 2 \\ -2 \\ 0 \\ 1 \end{bmatrix}$$

Thus, $W^\perp = \text{span}\{[0, 0, 1, 0]^T, [2, -2, 0, 1]^T\}$.

If you study the preceding example it becomes clear that finding the orthogonal complement of a set of vectors is equivalent to calculating the null space of a particular matrix. We have considerable experience in such calculations so this is a welcome observation.

Proposition 8.3.7.

If $S = \{v_1, v_2, \dots, v_k\} \subseteq \mathbb{R}^n$ and $A = [v_1|v_2|\dots|v_k]$ then $S^\perp = \text{Null}(A^T)$

Proof: Denote $A = [v_1|v_2|\dots|v_k] \in \mathbb{R}^{n \times k}$ and $x = [x_1, x_2, \dots, x_k]^T$. Observe that:

$$\begin{aligned} x \in \text{Null}(A^T) &\Leftrightarrow A^T x = 0 \\ &\Leftrightarrow [\text{row}_1(A^T)x, \text{row}_2(A^T)x, \dots, \text{row}_k(A^T)x] = 0 \\ &\Leftrightarrow [(col_1(A))^T x, (col_2(A))^T x, \dots, (col_k(A))^T x] = 0 \\ &\Leftrightarrow [v_1 \cdot x, v_2 \cdot x, \dots, v_k \cdot x] = 0 \\ &\Leftrightarrow v_j \cdot x = 0 \text{ for } j = 1, 2, \dots, k \\ &\Leftrightarrow x \in S^\perp \end{aligned}$$

Therefore, $\text{Null}(A^T) = S^\perp$. \square

Given the correspondence above we should be interested in statements which can be made about the row and column space of a matrix. It turns out there are two simple statements to be made in general:

Proposition 8.3.8.

Let $A \in \mathbb{R}^{m \times n}$ then

1. $\text{Null}(A^T) \perp \text{Col}(A)$.
2. $\text{Null}(A) \perp \text{Row}(A)$.

Proof: Let $S = \{col_1(A), col_2(A), \dots, col_n(A)\}$ and use Proposition 8.3.7 to deduce $S^\perp = \text{Null}(A^T)$. Therefore, each column of A is orthogonal to all vectors in $\text{Null}(A^T)$, in particular each column is orthogonal to the basis for $\text{Null}(A^T)$. Since the pivot columns are a basis for $\text{Col}(A)$ we can use Proposition 8.3.3 to conclude $\text{Null}(A^T) \perp \text{Col}(A)$.

To prove of (2.) apply (1.) to $B = A^T$ to deduce $\text{Null}(B^T) \perp \text{Col}(B)$. Hence, $\text{Null}((A^T)^T) \perp \text{Col}(A^T)$ and we find $\text{Null}(A) \perp \text{Col}(A^T)$. But, $\text{Col}(A^T) = \text{Row}(A)$ thus $\text{Null}(A) \perp \text{Row}(A)$. \square

The proof above makes ample use of previous work. I encourage the reader to try to prove this proposition from scratch. I don't think it's that hard and you might learn something. Just take an arbitrary element of each subspace and argue why the dot-product is zero.

Proposition 8.3.9.

Let $W_1, W_2 \leq \mathbb{R}^n$, if $W_1 \perp W_2$ then $W_1 \cap W_2 = \{0\}$

Proof: let $z \in W_1 \cap W_2$ then $z \in W_1$ and $z \in W_2$ and since $W_1 \perp W_2$ it follows $z \cdot z = 0$ hence $z = 0$ and $W_1 \cap W_2 \subseteq \{0\}$. The reverse inclusion $\{0\} \subseteq W_1 \cap W_2$ is clearly true since 0 is in every subspace. Therefore, $W_1 \cap W_2 = \{0\}$ \square

We defined the direct sum of two subspaces in the eigenvector chapter where we learned that the eigenspaces of a A decompose at least part of \mathbb{R}^n into a direct sum of invariant subspaces of L_A . If A was diagonalizable then the direct sum of the e-spaces covered all of \mathbb{R}^n . Just a reminder, now let's see how the direct sum is also of importance here:

Proposition 8.3.10.

Let $W \leq \mathbb{R}^n$ then

1. $\mathbb{R}^n = W \oplus W^\perp$.
2. $\dim(W) + \dim(W^\perp) = n$,
3. $(W^\perp)^\perp = W$,

Proof: Let $W \leq \mathbb{R}^n$ and choose an orthonormal basis $\beta = \{v_1, v_2, \dots, v_k\}$ for S . Let $z \in \mathbb{R}^n$ and define

$$Proj_W(z) = \sum_{i=1}^k (z \cdot v_i) v_i \quad \text{and} \quad Orth_W(z) = z - Proj_W(z).$$

Observe that $z = Proj_W(z) + Orth_W(z)$ and clearly $Proj_W(z) \in S$. We now seek to argue that $Orth_W(z) \in S^\perp$. Let $v_j \in \beta$ then

$$\begin{aligned} v_j \cdot Orth_W(z) &= v_j \cdot (z - Proj_W(z)) \\ &= v_j \cdot z - v_j \cdot \left(\sum_{i=1}^k (z \cdot v_i) v_i \right) \\ &= v_j \cdot z - \sum_{i=1}^k (z \cdot v_i) (v_j \cdot v_i) \\ &= v_j \cdot z - \sum_{i=1}^k (z \cdot v_i) \delta_{ij} \\ &= v_j \cdot z - z \cdot v_j \\ &= 0 \end{aligned}$$

Therefore, $\mathbb{R}^n = W \oplus W^\perp$. To prove (2.) notice we know by Proposition 8.3.5 that $W^\perp \leq \mathbb{R}^n$ and consequently there exists an orthonormal basis $\Gamma = \{w_1, w_2, \dots, w_l\}$ for W^\perp . Furthermore,

by Proposition 8.3.9 we find $\beta \cap \Gamma = \emptyset$ since 0 is not in either basis. We argue that $\beta \cup \Gamma$ is a basis for \mathbb{R}^n . Observe that $\beta \cup \Gamma$ clearly spans \mathbb{R}^n since $z = Proj_W(z) + Orth_W(z)$ for each $z \in \mathbb{R}^n$ and $Proj_W(z) \in span(\beta)$ while $Orth_W(z) \in span(\Gamma)$. Furthermore, I argue that $\beta \cup \Gamma$ is an orthonormal set. By construction β and Γ are orthonormal, so all we need prove is that the dot-product of vectors from β and Γ is zero, but that is immediate from the construction of Γ . We learned in Proposition 8.2.9 that orthogonality for set of nonzero vectors implies linearly independence. Hence, $\beta \cup \Gamma$ is a linearly independent spanning set for \mathbb{R}^n . By the dimension theorem we deduce that there must be n -vectors in $\beta \cup \Gamma$ since it must have the same number of vectors as any other basis for \mathbb{R}^n (the standard basis obviously has n -vectors). Therefore,

$$\dim(W) + \dim(W^\perp) = n.$$

in particular, we count $\dim(W^\perp) = n - k$ in my current notation. Now turn to ponder the proof of (3.). Let $z \in (W^\perp)^\perp$ and expand z in the basis $\beta \cup \Gamma$ to gain further insight, $z = z_1 v_1 + z_2 v_2 + \cdots + z_k v_k + z_{k+1} w_1 + z_{k+2} w_2 + \cdots + z_n w_{n-k}$. Since $z \in (W^\perp)^\perp$ then $z \cdot w_\perp = 0$ for all $w_\perp \in W^\perp$, in particular $z \cdot w_j = 0$ for all $j = 1, 2, \dots, n - k$. But, this implies $z_{k+1} = z_{k+2} = \cdots = z_n = 0$ since Proposition 8.2.26 showed the coordinates w.r.t. an orthonormal basis are given by dot-products. Therefore, $z \in span(\beta) = W$ and we have shown $(W^\perp)^\perp \subseteq W$. I invite the reader to prove the reverse inclusion to complete this proof. \square

Two items I defined for the purposes of the proof above have application far beyond the proof. Let's state them again for future reference. I give two equivalent definitions, technically we should prove that the second basis dependent statement follows from the first basis-independent statement. Primary definitions are as a point of mathematical elegance stated in a coordinate free language in as much as possible, however the second statement is far more useful.

Definition 8.3.11.

Let $W \leq \mathbb{R}^n$ if $z \in \mathbb{R}^n$ and $z = u + w$ for some $u \in W$ and $w \in W^\perp$ then we define $u = Proj_W(z)$ and $w = Orth_W(z)$. Equivalently, choose an orthonormal basis $\beta = \{v_1, v_2, \dots, v_k\}$ for W then if $z \in \mathbb{R}^n$ we define

$$Proj_W(z) = \sum_{i=1}^k (z \cdot v_i) v_i \quad \text{and} \quad Orth_W(z) = z - Proj_W(z).$$

Example 8.3.12. Let $W = span\{e_1 + e_2, e_3\}$ and $x = [1, 2, 3]^T$ calculate $Proj_W(x)$. To begin I note that the given spanning set is orthogonal and hence linear independent. We need only orthonormalize to obtain an orthonormal basis β for W

$$\beta = \{v_1, v_2\} \quad \text{with} \quad v_1 = \frac{1}{\sqrt{2}}[1, 1, 0]^T, \quad v_2 = [0, 0, 1]^T$$

Calculate, $v_1 \cdot x = \frac{3}{\sqrt{2}}$ and $v_2 \cdot x = 3$. Thus,

$$Proj_W([1, 2, 3]^T) = (v_1 \cdot x)v_1 + (v_2 \cdot x)v_2 = \frac{3}{\sqrt{2}}v_1 + 3v_2 = [\frac{3}{2}, \frac{3}{2}, 3]^T$$

Then it's easy to calculate the orthogonal part,

$$\text{Orth}_W([1, 2, 3]^T) = [1, 2, 3]^T - [\frac{3}{2}, \frac{3}{2}, 3]^T = [-\frac{1}{2}, \frac{1}{2}, 0]^T$$

As a check on the calculation note that $\text{Proj}_W(x) + \text{Orth}_W(x) = x$ and $\text{Proj}_W(x) \cdot \text{Orth}_W(x) = 0$.

Example 8.3.13. Let $W = \text{span}\{u_1, u_2, u_3\} \leq \mathbb{R}^{4 \times 1}$ where

$$u_1 = \begin{bmatrix} 2 \\ 1 \\ 2 \\ 0 \end{bmatrix} \quad u_2 = \begin{bmatrix} 0 \\ -2 \\ 1 \\ 1 \end{bmatrix} \quad u_3 = \begin{bmatrix} -1 \\ 2 \\ 0 \\ -1 \end{bmatrix}$$

calculate $\text{Proj}_W([0, 6, 0, 6]^T)$ ². Notice that the given spanning set appears to be linearly independent but it is not orthogonal. Apply Gram-Schmidt to fix it:

$$\begin{aligned} v_1 &= u_1 = [2, 1, 2, 0]^T \\ v_2 &= u_2 - \frac{u_2 \cdot v_1}{v_1 \cdot v_1} v_1 = u_2 = [0, -2, 1, 1]^T \\ v_3 &= u_3 - \frac{u_3 \cdot v_1}{v_1 \cdot v_1} v_1 - \frac{u_3 \cdot v_2}{v_2 \cdot v_2} v_2 = u_3 + \frac{5}{6} v_2 = [-1, 2, 0, -1]^T + [0, -\frac{10}{6}, \frac{5}{6}, \frac{5}{6}]^T \end{aligned}$$

We calculate,

$$v_3 = [-1, 2 - \frac{5}{3}, \frac{5}{6}, -1 + \frac{5}{6}]^T = [-1, \frac{1}{3}, \frac{5}{6}, -\frac{1}{6}]^T = \frac{1}{6}[-6, 2, 5, -1]^T$$

The normalized basis follows easily,

$$v'_1 = \frac{1}{3}[2, 1, 2, 0]^T \quad v'_2 = \frac{1}{\sqrt{6}}[0, -2, 1, 1]^T \quad v'_3 = \frac{1}{\sqrt{66}}[-6, 2, 5, -1]^T$$

Calculate dot-products in preparation for the projection calculation,

$$\begin{aligned} v'_1 \cdot x &= \frac{1}{3}[2, 1, 2, 0][0, 6, 0, 6]^T = 2 \\ v'_2 \cdot x &= \frac{1}{\sqrt{6}}[0, -2, 1, 1][0, 6, 0, 6]^T = \frac{1}{\sqrt{6}}(-12 + 6) = -\sqrt{6} \\ v'_3 \cdot x &= \frac{1}{\sqrt{66}}[-6, 2, 5, -1][0, 6, 0, 6]^T = \frac{1}{\sqrt{66}}(12 - 6) = \frac{6}{\sqrt{66}} \end{aligned}$$

Now we calculate the projection of $x = [0, 6, 0, 6]^T$ onto W with ease:

$$\begin{aligned} \text{Proj}_W(x) &= (x \cdot v'_1)v'_1 + (x \cdot v'_2)v'_2 + (x \cdot v'_3)v'_3 \\ &= (2)\frac{1}{3}[2, 1, 2, 0]^T - (\sqrt{6})\frac{1}{\sqrt{6}}[0, -2, 1, 1]^T + (\frac{6}{\sqrt{66}})\frac{1}{\sqrt{66}}[-6, 2, 5, -1]^T \\ &= [\frac{4}{3}, \frac{2}{3}, \frac{4}{3}, 0]^T + [0, 2, -1, -1]^T + [\frac{-6}{11}, \frac{2}{11}, \frac{5}{11}, \frac{-1}{11}]^T \\ &= [\frac{26}{33}, \frac{94}{33}, \frac{26}{33}, \frac{-36}{33}]^T \end{aligned}$$

and,

$$\text{Orth}_W(x) = [-\frac{26}{33}, \frac{104}{33}, \frac{-26}{33}, \frac{234}{33}]^T$$

²this problem is inspired from Anton & Rorres' §6.4 homework problem 3 part d.

8.4 the closest vector problem

Suppose we are given a subspace and a vector not in the subspace, which vector in the subspace is closest to the external vector? Naturally the projection answers this question. The projection of the external vector onto the subspace will be closest. Let me be a bit more precise:

Proposition 8.4.1. *Closest vector inequality.*

If $S \leq \mathbb{R}^n$ and $b \in \mathbb{R}^n$ such that $b \notin S$ then for all $u \in S$ with $u \neq \text{Proj}_S(b)$,

$$\|b - \text{Proj}_S(b)\| < \|b - u\|.$$

This means $\text{Proj}_S(b)$ is the closest vector to b in S .

Proof: Notice that $b - u = b - \text{Proj}_S(b) + \text{Proj}_S(b) - u$. Furthermore note that $b - \text{Proj}_S(b) = \text{Orth}_S(b) \in S^\perp$ whereas $\text{Proj}_S(b) - u \in S$ hence these are orthogonal vectors and we can apply the Pythagorean Theorem,

$$\|b - u\|^2 = \|b - \text{Proj}_S(b)\|^2 + \|\text{Proj}_S(b) - u\|^2$$

Notice that $u \neq \text{Proj}_S(b)$ implies $\text{Proj}_S(b) - u \neq 0$ hence $\|\text{Proj}_S(b) - u\|^2 > 0$. It follows that $\|b - \text{Proj}_S(b)\|^2 < \|b - u\|^2$. And as the $\|\cdot\|$ is nonnegative³ we can take the squareroot to obtain $\|b - \text{Proj}_S(b)\| < \|b - u\|$. \square

Remark 8.4.2.

In calculus III I show at least three distinct methods to find the point off a plane which is closest to the plane. We can minimize the distance function via the 2nd derivative test for two variables, or use Lagrange Multipliers or use the geometric solution which invokes the projection operator. It's nice that we have an explicit proof that the geometric solution is valid. We had argued on the basis of geometric intuition that $\text{Orth}_S(b)$ is the shortest vector from the plane S to the point b off the plane⁴ Now we have proof. Better yet, our proof equally well applies to subspaces of \mathbb{R}^n . In fact, this discussion extends to the context of inner product spaces.

Example 8.4.3. Consider $\mathbb{R}^{2 \times 1}$ let $S = \text{span}\{[1, 1]\}$. Find the point on the line S closest to the point $[4, 0]^T$.

$$\text{Proj}_S([4, 0]^T) = \frac{1}{2}([1, 1] \cdot [4, 0])[1, 1]^T = [2, 2]^T$$

Thus, $[2, 2]^T \in S$ is the closest point to $[4, 0]^T$. Geometrically, this is something you should have been able to derive for a few years now. The points $(2, 2)$ and $(4, 0)$ are on the perpendicular bisector of $y = x$ (the set S is nothing more than the line $y = x$ making the usual identification of points and vectors)

³notice $a^2 < b^2$ need not imply $a < b$ in general. For example, $(5)^2 < (-7)^2$ yet $5 \not< -7$. Generally, $a^2 < b^2$ together with the added condition $a, b > 0$ implies $a < b$.

Example 8.4.4. In Example 8.3.13 we found that $W = \text{span}\{u_1, u_2, u_3\} \leq \mathbb{R}^{4 \times 1}$ where

$$u_1 = \begin{bmatrix} 2 \\ 1 \\ 2 \\ 0 \end{bmatrix} \quad u_2 = \begin{bmatrix} 0 \\ -2 \\ 1 \\ 1 \end{bmatrix} \quad u_3 = \begin{bmatrix} -1 \\ 2 \\ 0 \\ -1 \end{bmatrix}$$

has $\text{Proj}_W([0, 6, 0, 6]^T) = [\frac{26}{33}, \frac{94}{33}, \frac{26}{33}, \frac{-36}{33}]^T$. We can calculate that

$$\text{rref} \left[\begin{array}{ccc|c} 2 & 0 & -1 & 0 \\ 1 & -2 & 2 & 6 \\ 2 & 1 & 0 & 0 \\ 0 & 1 & -1 & 6 \end{array} \right] = \left[\begin{array}{ccc|c} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{array} \right]$$

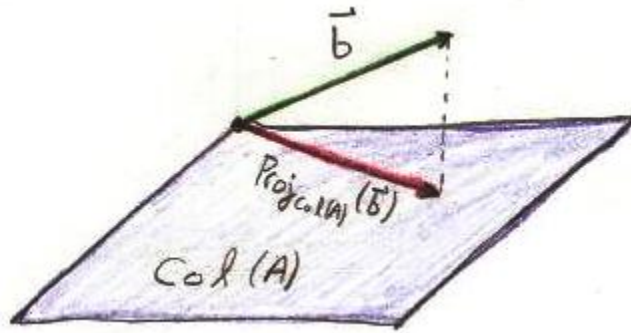
This means that $[0, 6, 0, 6]^T \notin W$. However, we learned in Proposition 8.4.1 that $\text{Proj}_W([0, 6, 0, 6]^T)$ is the vector in W which is closest to $[0, 6, 0, 6]^T$. Notice that we can deduce that the orthogonal basis from Example 8.3.13 unioned with $\text{Orth}_W([0, 6, 0, 6]^T)$ will form an orthogonal basis for $\mathbb{R}^{4 \times 1}$.

Example 8.4.5. Example 8.3.12 shows that $W = \text{span}\{e_1 + e_2, e_3\}$ and $x = [1, 2, 3]^T$ yields $\text{Proj}_W(x) = [\frac{3}{2}, \frac{3}{2}, 3]^T$. Again we can argue that $x \notin \text{Col}[e_1 + e_2 | e_3] = W$ but $\text{Proj}_W(x)$ is in fact in W . Moreover, $\text{Proj}_W(x)$ is the closest vector to x which is in W . In this case, the geometry is that $\text{Orth}_W(x) = [-\frac{1}{2}, \frac{1}{2}, 0]^T$ is the precisely the normal vector to the plane W .

The examples above are somewhat special in that the subspaces considered have only one dimension less than the total vector space. This means that the orthogonal projection of any vector outside the subspace will return the same vector modulo a nonzero constant. In other words, the orthogonal complement is selecting the normal vector to our subspace. In general if we had a subspace which was two or more dimensions smaller than the total vector space then there would be more variety in the output of the orthogonal projection with respect to the subspace. For example, if we consider a plane inside $\mathbb{R}^{4 \times 1}$ then there is more than just one direction which is orthogonal to the plane, the orthogonal projection would itself fill out a plane in $\mathbb{R}^{4 \times 1}$.

8.5 inconsistent equations

We've spent considerable time solving systems of equations which were *consistent*. What if a system of equations $Ax = b$ is inconsistent? What if anything can we say? Let $A \in \mathbb{R}^{m \times n}$ then we found in Proposition 5.6.3 $Ax = b$ is consistent iff $b \in \text{Col}(A)$. In other words, the system has a solution iff there is some linear combination of the columns of A such that we obtain b . Here the columns of A and b are both m -dimensional vectors. If $\text{rank}(A) = \dim(\text{Col}(A)) = m$ then the system is consistent no matter which choice for b is made. However, if $\text{rank}(A) < m$ then there are some vectors in $\mathbb{R}^{m \times 1}$ which are not in the column space of A and if $b \notin \text{Col}(A)$ then there will be no $x \in \mathbb{R}^n$ such that $Ax = b$. We can picture it as follows: the $\text{Col}(A)$ is a subspace of $\mathbb{R}^{m \times 1}$ and $b \in \mathbb{R}^{m \times 1}$ is a vector pointing out of the subspace. The shadow of b onto the subspace $\text{Col}(A)$ is given by $\text{Proj}_{\text{Col}(A)}(b)$.



Notice that $\text{Proj}_{\text{Col}(A)}(b) \in \text{Col}(A)$ thus the system $Ax = \text{Proj}_{\text{Col}(A)}(b)$ has a solution for any $b \in \mathbb{R}^{m \times 1}$. In fact, we can argue that x which solves $Ax = \text{Proj}_{\text{Col}(A)}(b)$ is the solution which comes closest to solving $Ax = b$. Closest in the sense that $\|Ax - b\|^2$ is minimized. We call such x the least squares solution to $Ax = b$ (*which is kind-of funny terminology since x is not actually a solution, perhaps we should really call it the "least squares approximation"*).

Proposition 8.5.1.

If $Ax = b$ is inconsistent then the solution of $Au = \text{Proj}_{\text{Col}(A)}(b)$ minimizes $\|Ax - b\|^2$.

Proof: We can break-up the vector b into a vector $\text{Proj}_{\text{Col}(A)}(b) \in \text{Col}(A)$ and $\text{Orth}_{\text{Col}(A)}(b) \in \text{Col}(A)^\perp$ where

$$b = \text{Proj}_{\text{Col}(A)}(b) + \text{Orth}_{\text{Col}(A)}(b).$$

Since $Ax = b$ is inconsistent it follows that $b \notin \text{Col}(A)$ thus $\text{Orth}_{\text{Col}(A)}(b) \neq 0$. Observe that:

$$\begin{aligned} \|Ax - b\|^2 &= \|Ax - \text{Proj}_{\text{Col}(A)}(b) - \text{Orth}_{\text{Col}(A)}(b)\|^2 \\ &= \|Ax - \text{Proj}_{\text{Col}(A)}(b)\|^2 + \|\text{Orth}_{\text{Col}(A)}(b)\|^2 \end{aligned}$$

Therefore, the solution of $Ax = Proj_{Col(A)}(b)$ minimizes $\|Ax - b\|^2$ since any other vector will make $\|Ax - Proj_{Col(A)}(b)\|^2 > 0$. \square

Admittably, there could be more than one solution of $Ax = Proj_{Col(A)}(b)$, however it is usually the case that this system has a unique solution. Especially for experimentally determined data sets.

We already have a technique to calculate projections and of course we can solve systems but it is exceedingly tedious to use the proposition above from scratch. Fortunately there is no need:

Proposition 8.5.2.

If $Ax = b$ is inconsistent then the solution(s) of $Au = Proj_{Col(A)}(b)$ are solutions of the so-called **normal equations** $A^T Au = A^T b$.

Proof: Observe that,

$$\begin{aligned}
 Au = Proj_{Col(A)}(b) &\Leftrightarrow b - Au = b - Proj_{Col(A)}(b) = Orth_{Col(A)}(b) \\
 &\Leftrightarrow b - Au \in Col(A)^\perp \\
 &\Leftrightarrow b - Au \in Null(A^T) \\
 &\Leftrightarrow A^T(b - Au) = 0 \\
 &\Leftrightarrow A^T Au = A^T b,
 \end{aligned}$$

where we used Proposition 8.3.8 in the third step. \square

The proposition below follows immediately from the preceding proposition.

Proposition 8.5.3.

If $\det(A^T A) \neq 0$ then there is a unique solution of $Au = Proj_{Col(A)}(b)$.

8.6 least squares analysis

In experimental studies we often have some model with coefficients which appear linearly. We perform an experiment, collect data, then our goal is to find coefficients which make the model fit the collected data. Usually the data will be inconsistent with the model, however we'll be able to use the idea of the last section to find the so-called *best-fit* curve. I'll begin with a simple linear model. This linear example contains all the essential features of the least-squares analysis.

8.6.1 linear least squares problem

Problem: find values of c_1, c_2 such that $y = c_1 x + c_2$ most closely models a given data set: $\{(x_1, y_1), (x_2, y_2), \dots, (x_k, y_k)\}$

Solution: Plug the data into the model and see what equations result:

$$y_1 = c_1x_1 + c_2, \quad y_2 = c_1x_2 + c_2, \quad \dots \quad y_k = c_1x_k + c_2$$

arrange these as a matrix equation,

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_k \end{bmatrix} = \begin{bmatrix} x_1 & 1 \\ x_2 & 1 \\ \vdots & \vdots \\ x_k & 1 \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} \Rightarrow \vec{y} = M\vec{v}$$

where $\vec{y} = [y_1, y_2, \dots, y_k]^T$, $v = [c_1, c_2]^T$ and M is defined in the obvious way. The system $\vec{y} = M\vec{v}$ will be inconsistent due to the fact that error in the data collection will⁵ make the results bounce above and below the true solution. We can solve the normal equations $M^T\vec{y} = M^TM\vec{v}$ to find c_1, c_2 which give the best-fit curve⁶.

Example 8.6.1. Find the best fit line through the points $(0, 2), (1, 1), (2, 4), (3, 3)$. Our model is $y = c_1 + c_2x$. Assemble M and \vec{y} as in the discussion preceding this example:

$$\vec{y} = \begin{bmatrix} 2 \\ 1 \\ 4 \\ 3 \end{bmatrix} \quad M = \begin{bmatrix} 0 & 1 \\ 1 & 1 \\ 2 & 1 \\ 3 & 1 \end{bmatrix} \quad \Rightarrow \quad M^TM = \begin{bmatrix} 0 & 1 & 2 & 3 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 1 & 1 \\ 2 & 1 \\ 3 & 1 \end{bmatrix} = \begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix}$$

$$\text{and we calculate:} \quad M^Ty = \begin{bmatrix} 0 & 1 & 2 & 3 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \\ 4 \\ 3 \end{bmatrix} = \begin{bmatrix} 18 \\ 10 \end{bmatrix}$$

The normal equations⁷ are $M^TM\vec{v} = M^T\vec{y}$. Note that $(M^TM)^{-1} = \frac{1}{20} \begin{bmatrix} 4 & -6 \\ -6 & 14 \end{bmatrix}$ thus the solution of the normal equations is simply,

$$\vec{v} = (M^TM)^{-1}M^T\vec{y} = \frac{1}{20} \begin{bmatrix} 4 & -6 \\ -6 & 14 \end{bmatrix} \begin{bmatrix} 18 \\ 10 \end{bmatrix} = \begin{bmatrix} \frac{3}{10} \\ \frac{3}{5} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix}$$

Thus, $\boxed{y = 0.6x + 1.6}$ is the best-fit line. This solution minimizes the vertical distances squared between the data and the model.

It's really nice that the order of the normal equations is only as large as the number of coefficients in the model. If the order depended on the size of the data set this could be much less fun for

⁵almost always

⁶notice that if x_i are not all the same then it is possible to show $\det(M^TM) \neq 0$ and then the solution to the normal equations is unique

⁷notice my choice to solve this system of 2 equations and 2 unknowns is just a choice, You can solve it a dozen different ways, you do it the way which works best for you.

real-world examples. Let me set-up the linear least squares problem for 3-coefficients and data from \mathbb{R}^3 , the set-up for more coefficients and higher-dimensional data is similar. We already proved this in general in the last section, the proposition simply applies mathematics we already derived. I state it for your convenience.

Proposition 8.6.2.

Given data $\{\vec{r}_1, \vec{r}_2, \dots, \vec{r}_n\} \subset \mathbb{R}^3$, with $\vec{r}_k = [x_k, y_k, z_k]^T$, the best-fit of the linear model $z = c_1x + c_2y + c_3$ is obtained by solving the normal equations $M^T M \vec{v} = M^T \vec{z}$ where

$$\vec{z} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} \quad M = \begin{bmatrix} x_1 & y_1 & 1 \\ x_2 & y_2 & 1 \\ \vdots & \vdots & \vdots \\ x_n & y_n & 1 \end{bmatrix} \quad \vec{z} = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix}.$$

Example 8.6.3. Find the plane which is closest to the points $(0, 0, 0), (1, 2, 3), (4, 0, 1), (0, 3, 0), (1, 1, 1)$. An arbitrary⁸ plane has the form $z = c_1x + c_2y + c_3$. Work on the normal equations,

$$M = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 2 & 1 \\ 4 & 0 & 1 \\ 0 & 3 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad \vec{z} = \begin{bmatrix} 0 \\ 3 \\ 1 \\ 0 \\ 1 \end{bmatrix} \Rightarrow M^T M = \begin{bmatrix} 0 & 1 & 4 & 0 & 1 \\ 0 & 2 & 0 & 3 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0 & 0 & 1 \\ 1 & 2 & 1 \\ 4 & 0 & 1 \\ 0 & 3 & 1 \\ 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 18 & 3 & 6 \\ 3 & 14 & 6 \\ 6 & 6 & 5 \end{bmatrix}$$

$$\text{also, } M^T \vec{z} = \begin{bmatrix} 0 & 1 & 4 & 0 & 1 \\ 0 & 2 & 0 & 3 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 3 \\ 1 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 8 \\ 7 \\ 5 \end{bmatrix}$$

We solve $M^T M \vec{v} = M^T \vec{z}$ by row operations, after some calculation we find:

$$\text{rref}[M^T M | M^T \vec{z}] = \left[\begin{array}{ccc|c} 1 & 0 & 1 & 89/279 \\ 0 & 1 & 1 & 32/93 \\ 0 & 0 & 1 & 19/93 \end{array} \right] \Rightarrow \begin{array}{l} c_1 = 89/279 \\ c_2 = 32/93 \\ c_3 = 19/93 \end{array}$$

Therefore, $z = \frac{89}{293}x + \frac{32}{93}y + \frac{19}{93}$ is the plane which is "closest" to the given points. Technically, I'm not certain that is is the absolute closest. We used the vertical distance squared as a measure of distance from the point. Distance from a point to the plane is measured along the normal direction, so there is no guarantee this is really the absolute "best" fit. For the purposes of this course we will ignore this subtle and annoying point. When I say "best-fit" I mean the least squares fit of the model.

⁸technically, the general form for a plane is $ax + by + cz = d$, if $c = 0$ for the best solution then our model misses it. In such a case we could let x or y play the role that z plays in our set-up.

8.6.2 nonlinear least squares

Problem: find values of c_1, c_2 such that $y = c_1 f_1(x) + c_2 f_2(x) + \cdots + c_n f_n(x)$ most closely models a given data set: $\{(x_1, y_1), (x_2, y_2), \dots, (x_k, y_k)\}$. We assume the coefficients c_1, c_2 appear linearly on (possibly nonlinear) functions f_1, f_2, \dots, f_n .

Solution: Plug the data into the model and see what equations result:

$$\begin{aligned} y_1 &= c_1 f_1(x_1) + c_2 f_2(x_1) + \cdots + c_n f_n(x_1), \\ y_2 &= c_1 f_1(x_2) + c_2 f_2(x_2) + \cdots + c_n f_n(x_2), \\ &\vdots \quad \quad \quad \vdots \\ y_k &= c_1 f_1(x_k) + c_2 f_2(x_k) + \cdots + c_n f_n(x_k) \end{aligned}$$

arrange these as a matrix equation,

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_k \end{bmatrix} = \begin{bmatrix} f_1(x_1) & f_2(x_1) & \cdots & f_n(x_1) \\ f_1(x_2) & f_2(x_2) & \cdots & f_n(x_2) \\ \vdots & \vdots & \ddots & \vdots \\ f_1(x_k) & f_2(x_k) & \cdots & f_n(x_k) \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{bmatrix} \Rightarrow \vec{y} = M\vec{v}$$

where $\vec{y} = [y_1, y_2, \dots, y_k]^T$, $\vec{v} = [c_1, c_2, \dots, c_n]^T$ and M is defined in the obvious way. The system $\vec{y} = M\vec{v}$ will be inconsistent due to the fact that error in the data collection will⁹ make the results bounce above and below the true solution. We can solve the normal equations $M^T \vec{y} = M^T M \vec{v}$ to find c_1, c_2, \dots, c_n which give the best-fit curve¹⁰.

Remark 8.6.4.

Nonlinear least squares includes the linear case as a subcase, take $f_1(x) = x$ and $f_2(x) = 1$ and we return to the linear least squares examples. We will use data sets from \mathbb{R}^2 in this subsection. These techniques do extend to data sets with more variables as I demonstrated in the simple case of a plane.

Example 8.6.5. Find the best-fit parabola through the data $(0, 0), (1, 3), (4, 4), (3, 6), (2, 2)$. Our model has the form $y = c_1 x^2 + c_2 x + c_3$. Identify that $f_1(x) = x^2$, $f_2(x) = x$ and $f_3(x) = 1$ thus we should study the normal equations: $M^T M \vec{v} = M^T \vec{y}$ where:

$$M = \begin{bmatrix} f_1(0) & f_2(0) & f_3(0) \\ f_1(1) & f_2(1) & f_3(1) \\ f_1(4) & f_2(4) & f_3(4) \\ f_1(3) & f_2(3) & f_3(3) \\ f_1(2) & f_2(2) & f_3(2) \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 1 & 1 \\ 16 & 4 & 1 \\ 9 & 3 & 1 \\ 4 & 2 & 1 \end{bmatrix} \quad \text{and} \quad \vec{y} = \begin{bmatrix} 0 \\ 3 \\ 4 \\ 6 \\ 2 \end{bmatrix}.$$

⁹almost always

¹⁰notice that if $f_j(x_i)$ are not all the same then it is possible to show $\det(M^T M) \neq 0$ and then the solution to the normal equations is unique

Hence, calculate

$$M^T M = \begin{bmatrix} 0 & 1 & 16 & 9 & 4 \\ 0 & 1 & 4 & 3 & 2 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0 & 0 & 1 \\ 1 & 1 & 1 \\ 16 & 4 & 1 \\ 9 & 3 & 1 \\ 4 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 354 & 100 & 30 \\ 100 & 30 & 10 \\ 30 & 10 & 5 \end{bmatrix}$$

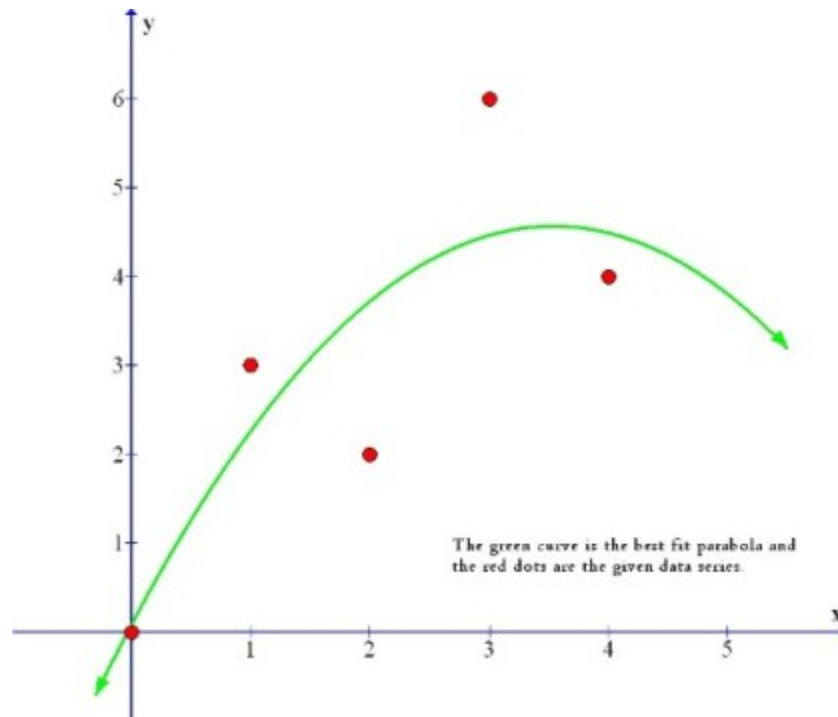
and,

$$M^T \vec{y} = \begin{bmatrix} 0 & 1 & 16 & 9 & 4 \\ 0 & 1 & 4 & 3 & 2 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 3 \\ 4 \\ 6 \\ 2 \end{bmatrix} = \begin{bmatrix} 129 \\ 41 \\ 15 \end{bmatrix}$$

After a few row operations we can deduce,

$$\text{rref}[M^T M | M^T \vec{y}] = \left[\begin{array}{ccc|c} 1 & 0 & 1 & -5/14 \\ 0 & 1 & 1 & 177/70 \\ 0 & 0 & 1 & 3/35 \end{array} \right] \Rightarrow \begin{array}{l} c_1 = -5/14 \approx -0.357 \\ c_2 = 177/70 \approx 2.529 \\ c_3 = 3/35 = 0.086 \end{array}$$

We find the best-fit parabola is $y = -0.357x^2 + 2.529x + 0.086$



Yes..., but what's this for?

Example 8.6.6. Suppose you land on a mysterious planet. You find that if you throw a ball it's height above the ground y at time t is measured at times $t = 0, 1, 2, 3, 4$ seconds to be $y = 0, 2, 3, 6, 4$ meters respective. Assume that Newton's Law of gravity holds and determine the gravitational acceleration from the data. We already did the math in the last example. Newton's law approximated for heights near the surface of the planet simply says $y'' = -g$ which integrates twice to yield $y(t) = -gt^2/2 + v_o t + y_0$ where v_o is the initial velocity in the vertical direction. We find the best-fit parabola through the data set $\{(0, 0), (1, 3), (4, 4), (3, 6), (2, 2)\}$ by the math in the last example,

$$y(t) = -0.357t^2 + 2.529 + 0.086$$

we deduce that $g = 2(0.357)m/s^2 = 0.714m/s^2$. Apparently the planet is smaller than Earth's moon (which has $g_{moon} \approx \frac{1}{6}9.8m/s^2 = 1.63m/s^2$).

Remark 8.6.7.

If I know for certain that the ball is at $y = 0$ at $t = 0$ would it be equally reasonable to assume y_o in our model? If we do it simplifies the math. The normal equations would only be order 2 in that case.

Example 8.6.8. Find the best-fit parabola that passes through the origin and the points $(1, 3), (4, 4), (3, 6), (2, 2)$. To begin we should state our model: since the parabola goes through the origin we know the y -intercept is zero hence $y = c_1x^2 + c_2x$. Identify $f_1(x) = x^2$ and $f_2(x) = x$. As usual set-up the M and \vec{y} ,

$$M = \begin{bmatrix} f_1(1) & f_2(1) \\ f_1(4) & f_2(4) \\ f_1(3) & f_2(3) \\ f_1(2) & f_2(2) \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 16 & 4 \\ 9 & 3 \\ 4 & 2 \end{bmatrix} \quad \text{and} \quad \vec{y} = \begin{bmatrix} 3 \\ 4 \\ 6 \\ 2 \end{bmatrix}.$$

Calculate,

$$M^T M = \begin{bmatrix} 1 & 16 & 9 & 4 \\ 1 & 4 & 3 & 2 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 16 & 4 \\ 9 & 3 \\ 4 & 2 \end{bmatrix} = \begin{bmatrix} 354 & 100 \\ 100 & 30 \end{bmatrix} \Rightarrow (M^T M)^{-1} = \frac{1}{620} \begin{bmatrix} 30 & -100 \\ -100 & 354 \end{bmatrix}$$

and,

$$M^T \vec{y} = \begin{bmatrix} 1 & 16 & 9 & 4 \\ 1 & 4 & 3 & 2 \end{bmatrix} \begin{bmatrix} 3 \\ 4 \\ 6 \\ 2 \end{bmatrix} = \begin{bmatrix} 129 \\ 41 \end{bmatrix}$$

We solve $M^T M \vec{v} = M^T \vec{y}$ by multiplying both sides by $(M^T M)^{-1}$ which yeilds,

$$\vec{v} = (M^T M)^{-1} M^T \vec{y} = \frac{1}{620} \begin{bmatrix} 30 & -100 \\ -100 & 354 \end{bmatrix} \begin{bmatrix} 129 \\ 41 \end{bmatrix} = \begin{bmatrix} -23/62 \\ 807/310 \end{bmatrix} \Rightarrow \begin{matrix} c_1 = -23/62 \approx -0.371 \\ c_2 = 807/310 \approx 2.603 \end{matrix}$$

Thus the best-fit parabola through the origin is $y = -0.371x^2 + 2.603x$

Sometimes an application may not allow for direct implementation of the least squares method, however a rewrite of the equations makes the unknown coefficients appear linearly in the model.

Example 8.6.9. *Newton's Law of Cooling states that an object changes temperature T at a rate proportional to the difference between T and the room-temperature. Suppose room temperature is known to be 70° then $dT/dt = -k(T - 70) = -kT + 70k$. Calculus reveals solutions have the form $T(t) = c_0 e^{-kt} + 70$. Notice this is very intuitive since $T(t) \rightarrow 70$ for $t \gg 0$. Suppose we measure the temperature at successive times and we wish to find the best model for the temperature at time t . In particular we measure: $T(0) = 100$, $T(1) = 90$, $T(2) = 85$, $T(3) = 83$, $T(4) = 82$. One unknown coefficient is k and the other is c_1 . Clearly k does not appear linearly. We can remedy this by working out the model for the natural log of $T - 70$. Properties of logarithms will give us a model with linearly appearing unknowns:*

$$\ln(T(t) - 70) = \ln(c_0 e^{-kt}) = \ln(c_0) + \ln(e^{-kt}) = \ln(c_0) - kt$$

Let $c_1 = \ln(c_0)$, $c_2 = -k$ then identify $f_1(t) = 1$ while $f_2(t) = t$ and $y = \ln(T(t) - 70)$. Our model is $y = c_1 f_1(t) + c_2 f_2(t)$ and the data can be generated from the given data for $T(t)$:

$$\begin{aligned} t_1 = 0 : y_1 &= \ln(T(0) - 70) = \ln(100 - 70) = \ln(30) \\ t_2 = 1 : y_2 &= \ln(T(1) - 70) = \ln(90 - 70) = \ln(20) \\ t_3 = 2 : y_3 &= \ln(T(2) - 70) = \ln(85 - 70) = \ln(15) \\ t_4 = 3 : y_4 &= \ln(T(3) - 70) = \ln(83 - 70) = \ln(13) \\ t_5 = 4 : y_5 &= \ln(T(4) - 70) = \ln(82 - 70) = \ln(12) \end{aligned}$$

Our data for (t, y) is $(0, \ln 30)$, $(1, \ln 20)$, $(2, \ln 15)$, $(3, \ln 13)$, $(4, \ln 12)$. We should solve normal equations $M^T M \vec{v} = M^T \vec{y}$ where

$$M = \begin{bmatrix} f_1(0) & f_2(0) \\ f_1(1) & f_2(1) \\ f_1(2) & f_2(2) \\ f_1(3) & f_2(3) \\ f_1(4) & f_2(4) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \\ 1 & 3 \\ 1 & 4 \end{bmatrix} \quad \text{and} \quad \vec{y} = \begin{bmatrix} \ln 30 \\ \ln 20 \\ \ln 15 \\ \ln 13 \\ \ln 12 \end{bmatrix}.$$

We can calculate $M^T M = \begin{bmatrix} 5 & 10 \\ 10 & 30 \end{bmatrix}$ and $M^T \vec{y} \approx \begin{bmatrix} 14.15 \\ 26.05 \end{bmatrix}$. Solve $M^T M \vec{v} = M^T \vec{y}$ by multiplication by inverse of $M^T M$:

$$\vec{y} = (M^T M)^{-1} M^T \vec{y} = \begin{bmatrix} 3.284 \\ -0.2263 \end{bmatrix} \Rightarrow \begin{matrix} c_1 \approx 3.284 \\ c_2 \approx -0.2263 \end{matrix}.$$

Therefore, $y(t) = \ln(T(t) - 70) = 3.284 - 0.2263t$ we identify that $k = 0.2263$ and $\ln(c_0) = 3.284$ which yields $c_0 = e^{3.284} = 26.68$. We find the best-fit temperature function is

$$\boxed{T(t) = 26.68e^{-0.2263t} + 70.}$$

Now we could give good estimates for the temperature $T(t)$ for other times. If Newton's Law of cooling is an accurate model and our data was collected carefully then we ought to be able to make accurate predictions with our model.

Remark 8.6.10.

The accurate analysis of data is more involved than my silly examples reveal here. Each experimental fact comes with an error which must be accounted for. A real experimentalist never gives just a number as the answer. Rather, one must give a number and an uncertainty or error. There are ways of accounting for the error of various data. Our approach here takes all data as equally valid. There are weighted best-fits which minimize a weighted least squares. Technically, this takes us into the realm of math of inner-product spaces. Finite dimensional inner-product spaces also allows for least-norm analysis. The same philosophy guides the analysis: the square of the norm measures the sum of the squares of the errors in the data. The collected data usually does not precisely fit the model, thus the equations are inconsistent. However, we project the data onto the plane representative of model solutions and this gives us the best model for our data. Generally we would like to minimize χ^2 , this is the notation for the sum of the squares of the error often used in applications. In statistics finding the best-fit line is called doing "linear regression".

8.7 orthogonal matrices and the QR factorization

In principle the material in this section could be covered before previous sections. I include it here in part to help the students avoid double printing in Fall 2010. Probably I will move this material early in the chapter in future versions. Moreover, it is entirely likely I lecture on aspects of this section before I cover least squares.

Suppose we have an orthogonal basis $\beta = \{v_1, v_2, \dots, v_n\}$ for \mathbb{R}^n . Let's investigate the properties of the matrix of this basis. Note that $\|v_j\| \neq 0$ for each j since β is linearly independent set of vectors. Moreover, if we denote $\|v_j\| = l_j$ then we can compactly summarize orthogonality of β with the following relation:

$$v_j \cdot v_k = l_j^2 \delta_{jk}.$$

As a matrix equation we recognize that $[v_j]^T v_k$ is also the jk -th component of the product of $[\beta]^T$ and $[\beta]$. Let me expand on this in matrix notation:

$$[\beta]^T [\beta] = \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_n^T \end{bmatrix} [v_1 | v_2 | \dots | v_n] = \begin{bmatrix} v_1^T v_1 & v_1^T v_2 & \dots & v_1^T v_n \\ v_2^T v_1 & v_2^T v_2 & \dots & v_2^T v_n \\ \vdots & \vdots & \dots & \vdots \\ v_n^T v_1 & v_n^T v_2 & \dots & v_n^T v_n \end{bmatrix} = \begin{bmatrix} l_1^2 & 0 & \dots & 0 \\ 0 & l_2^2 & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ 0 & 0 & \dots & l_n^2 \end{bmatrix}$$

This means that $[\beta]^T$ is almost the inverse of $[\beta]$. Observe if we had $l_j = 1$ for $j = 1, 2, \dots, n$ then $[\beta]^T = [\beta]^{-1}$. In other words, if we use an orthonormal basis then the inverse of the basis matrix is obtained by transposition. In fact, matrices with this property have a name:

Definition 8.7.1.

Let $A \in \mathbb{R}^{n \times n}$ then we say that A is an **orthogonal matrix** iff $A^T A = I$. The set of all orthogonal $n \times n$ matrices is denoted $O(n)$.

The discussion preceding the definition provides a proof for the following proposition:

Proposition 8.7.2. matrix of an orthonormal basis is an orthogonal matrix

If β is an orthonormal basis then $[\beta]^T [\beta] = I$ or equivalently $[\beta]^T = [\beta]^{-1}$.

So far we have considered only bases for all of \mathbb{R}^n but we can also find similar results for a subspace $W \leq \mathbb{R}^n$. Suppose $\dim(W) < n$. If β is an orthonormal basis for W then it is still true that $[\beta]^T [\beta] = I_{\dim(W)}$ however since $[\beta]$ is not a square matrix it does not make sense to say that $[\beta]^T = [\beta]^{-1}$. The QR -factorization of a matrix is tied to this discussion.

Proposition 8.7.3. QR factorization of a full-rank matrix

If $A \in \mathbb{R}^{m \times n}$ is a matrix with linearly independent columns then there exists a matrix $Q \in \mathbb{R}^{m \times n}$ whose columns form an orthonormal basis for $\text{Col}(A)$ and square matrix $R \in \mathbb{R}^{n \times n}$ which is upper triangular and has $R_{ii} > 0$ for $i = 1, 2, \dots, n$.

Proof: begin by performing the Gram-Schmidt procedure on the columns of A . Next, normalize that orthogonal basis to obtain an orthonormal basis $\beta = \{u_1, u_2, \dots, u_n\}$ for $Col(A)$. Note that since each column in A is in $Col(A)$ it follows that some linear combination of the vectors in β will produce that column;

$$col_j(A) = R_{1j}u_1 + R_{2j}u_2 + \dots + R_{nj}u_n = [u_1|u_2|\dots|u_n][R_{1j}, R_{2j}, \dots, R_{nj}]^T$$

for some constants $R_{1j}, R_{2j}, \dots, R_{nj} \in \mathbb{R}$. Let R be the matrix formed from the coefficients of the linear combinations that link columns of A and the orthonormal basis; in particular define R such that $col_j(R) = (R_{1j}, R_{2j}, \dots, R_{nj})$. It follows that if we denote $[\beta] = Q$ we have for each $j = 1, 2, \dots, n$ the relation

$$col_j(A) = Q col_j(R)$$

Hence,

$$A = [col_1(A)|col_2(A)|\dots|col_n(A)] = [Q col_1(R)|Q col_2(R)|\dots|Q col_n(R)]$$

and we find by the concatenation proposition

$$A = Q[col_1(R)|col_2(R)|\dots|col_n(R)] = QR$$

where $R \in \mathbb{R}^{n \times n}$ as we wished. It remains to show that R is upper triangular with positive diagonal entries. Recall how Gram-Schmidt is accomplished (I'll do normalization along side the orthogonalization for the purposes of this argument). We began by defining $u_1 = \frac{1}{\|col_1(A)\|} col_1(A)$ hence $col_1(A) = \|col_1(A)\|u_1$ and we identify that $col_1(R) = (\|col_1(A)\|, 0, \dots, 0)$. The next step in the algorithm is to define u_2 by calculating v_2 (since we normalized $u_1 \cdot u_1 = 1$)

$$v_2 = col_2(A) - (col_2(A) \cdot u_1)u_1$$

and normalizing (I define l_2 in the last equality below)

$$u_2 = \frac{1}{\|col_2(A) - (col_2(A) \cdot u_1)u_1\|} v_2 = \frac{1}{l_2} v_2$$

In other words, $l_2 u_2 = v_2 = col_2(A) - (col_2(A) \cdot u_1)u_1$ hence

$$col_2(A) = l_2 u_2 + (col_2(A) \cdot u_1)u_1$$

From which we can read the second column of R as

$$col_2(R) = (-(col_2(A) \cdot u_1), l_2, 0, \dots, 0).$$

Continuing in this fashion, if we define l_j to be the length of the orthogonalization of $col_j(A)$ with respect to the preceding $\{u_1, u_2, \dots, u_{j-1}\}$ orthonormal vectors then a calculation similar to the one just performed will reveal that

$$col_j(R) = (\star, \dots, \star, l_j, 0, \dots, 0)$$

and \star are possibly nonzero components in rows 1 through $j - 1$ of the column vector and l_j is the j -th component which is necessarily positive since it is the length of some nonzero vector. Put all of this together and we find that R is upper triangular with positive diagonal entries¹¹. \square

Very well, we now know that a QR -factorization exists for a matrix with LI columns. This leaves us with two natural questions:

1. how do we calculate the factorization of a given matrix A ?
2. what is the use of the QR factorization ?

We will answer (1.) with an example or two and I will merely scratch the surface for question (2.). If you took a serious numerical linear algebra course then it is likely you would delve deeper.

Example 8.7.4. *I make use of Example 8.2.25 to illustrate how to find the QR -factorization of a matrix. Basically once you find the Gram-Schmidt then it is as simple as multiplying the orthonormalized column vectors and the matrix since $A = QR$ implies $R = Q^T A$.*

¹¹see Lay pg. 405-406 if you don't like my proof

Using Ex. 8.2.25

$$A = \begin{bmatrix} 1 & 1 & 0 & 3 \\ 0 & 1 & 0 & 2 \\ 1 & 1 & 2 & 0 \\ 1 & 1 & 3 & 3 \end{bmatrix}$$

Illustrating How
to calculate
QR-factorization
of A

Gram.-Schmidt

$$Q = \begin{bmatrix} 1/\sqrt{3} & 0 & -5/\sqrt{42} & 1/\sqrt{14} \\ 0 & 1 & 0 & 0 \\ 1/\sqrt{3} & 0 & 1/\sqrt{42} & -3/\sqrt{14} \\ 1/\sqrt{3} & 0 & 1/\sqrt{42} & 2/\sqrt{14} \end{bmatrix}$$

Trying to find R such that $A = QR$ Instead, solve $Q^T A = Q^T Q R = R$

$$\begin{aligned} R = Q^T A &= \begin{bmatrix} 1/\sqrt{3} & 0 & 1/\sqrt{3} & 1/\sqrt{3} \\ 0 & 1 & 0 & 0 \\ -5/\sqrt{42} & 0 & 1/\sqrt{42} & 4/\sqrt{42} \\ 1/\sqrt{14} & 0 & -3/\sqrt{14} & 2/\sqrt{14} \end{bmatrix} \begin{bmatrix} 1 & 1 & 0 & 3 \\ 0 & 1 & 0 & 2 \\ 1 & 1 & 2 & 0 \\ 1 & 1 & 3 & 3 \end{bmatrix} \\ &= \begin{bmatrix} 3/\sqrt{3} & 3/\sqrt{3} & 5/\sqrt{3} & 6/\sqrt{3} \\ 0 & 1 & 0 & 2 \\ 0 & 0 & 14/\sqrt{42} & -3/\sqrt{42} \\ 0 & 0 & 0 & 9/\sqrt{14} \end{bmatrix} \end{aligned}$$

as advertised, upper Δ
with positive diagonals!

Finally, returning to (2.). One nice use of the QR-factorization is to simplify calculation of the normal equations. We sought to solve $A^T A u = A^T b$. Suppose that $A = QR$ to obtain:

$$(QR)^T (QR)u = (QR)^T b \Rightarrow R^T Q^T Q R u = R^T Q^T b \Rightarrow \boxed{Ru = Q^T b}.$$

This problem is easily solved by back-substitution since R is upper-triangular. I may ask you a homework to examine this in more detail for a specific example.

8.8 orthogonal transformations and geometry

If we begin with an orthogonal subset of \mathbb{R}^n and we perform a linear transformation then will the image of the set still be orthogonal? We would like to characterize linear transformations which maintain orthogonality. These transformations should take an orthogonal basis to a new basis which is still orthogonal.

Definition 8.8.1.

If $T : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is a linear transformation such that $T(x) \cdot T(y) = x \cdot y$ for all $x, y \in \mathbb{R}^n$ then we say that T is an **orthogonal transformation**

Example 8.8.2. Let $\{e_1, e_2\}$ be the standard basis for $\mathbb{R}^{2 \times 1}$ and let $R(\theta) = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$ be a rotation of the coordinates by angle θ in the clockwise direction,

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x \cos \theta + y \sin \theta \\ -x \sin \theta + y \cos \theta \end{bmatrix}$$

As a check on my sign conventions, consider rotating $[1, 0]^T$ by $R(\pi/2)$, we obtain $[x', y']^T = [0, 1]$. See the picture for how to derive these transformations from trigonometry. Intuitively, a rotation should not change the length of a vector, let's check the math: let $v, w \in \mathbb{R}^{2 \times 1}$,

$$\begin{aligned} R(\theta)v \cdot R(\theta)w &= [R(\theta)v]^T R(\theta)w \\ &= v^T R(\theta)^T R(\theta)w \end{aligned}$$

Now calculate $R(\theta)^T R(\theta)$,

$$R(\theta)^T R(\theta) = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} = \begin{bmatrix} \cos^2 \theta + \sin^2 \theta & 0 \\ 0 & \sin^2 \theta + \cos^2 \theta \end{bmatrix} = I$$

Therefore, $R(\theta)v \cdot R(\theta)w = v^T I w = v^T w = v \cdot w$ for all $v, w \in \mathbb{R}^{2 \times 1}$ and we find $L_{R(\theta)}$ is an orthogonal transformation.

This shows the matrix of a rotation L_R satisfies $R^T R = I$. Is this always true or was this just a special formula for rotations? Or is this just a two-dimensional thing? What if we look at orthogonal transformations on \mathbb{R}^n what general condition is there on the matrix of the transformation?

Definition 8.8.3.

Let $A \in \mathbb{R}^{n \times n}$ then we say that A is an **orthogonal matrix** iff $A^T A = I$. Moreover, we say A is a **reflection matrix** if A is orthogonal and $\det(A) = -1$ whereas we say A is a **rotation matrix** if A is orthogonal with $\det(A) = 1$. The set of all orthogonal $n \times n$ matrices is denoted $O(n)$ and the set of all $n \times n$ rotation matrices is denoted $SO(n)$.

Proposition 8.8.4. matrix of an orthogonal transformation is orthogonal

If A is the matrix of an orthogonal transformation on \mathbb{R}^n then $A^T A = I$ and either A is a rotation matrix or A is a reflection matrix.

Proof: Suppose $L(x) = Ax$ and L is an orthogonal transformation on \mathbb{R}^n . Notice that

$$L(e_i) \cdot L(e_j) = [Ae_i]^T Ae_j = e_i^T [A^T A] e_j$$

and

$$e_i \cdot e_j = e_i^T e_j = e_i^T I e_j$$

hence $e_i^T [A^T A - I] e_j = 0$ for all i, j thus $A^T A - I = 0$ by Example 3.7.11 and we find $A^T A = I$. Following a homework you did earlier in the course,

$$\det(A^T A) = \det(I) \Leftrightarrow \det(A)\det(A) = 1 \Leftrightarrow \det(A) = \pm 1$$

Thus $A \in SO(n)$ or A is a reflection matrix. \square

The proposition below is immediate from the definitions of length, angle and linear transformation.

Proposition 8.8.5. orthogonal transformations preserve lengths and angles

If $v, w \in \mathbb{R}^n$ and L is an orthogonal transformation such that $v' = L(v)$ and $w' = L(w)$ then the angle between v' and w' is the same as the angle between v and w , in addition the length of v' is the same as v .

Remark 8.8.6.

Reflections, unlike rotations, will spoil the "handedness" of a coordinate system. If we take a right-handed coordinate system and perform a reflection we will obtain a new coordinate system which is left-handed. If you'd like to know more just ask me sometime.

If orthogonal transformations preserve the geometry of \mathbb{R}^n you might wonder if there are other non-linear transformations which also preserve distance and angle. The answer is yes, but we need to be careful to distinguish between the length of a vector and the distance between points. It turns out that the translation defined below will preserve the distance, but not the norm or length of a vector.

Definition 8.8.7.

Fix $b \in \mathbb{R}^n$ then a translation by b is the mapping $T_b(x) = x + b$ for all $x \in \mathbb{R}^n$.

This is known as an **affine transformation**, it is not linear since $T(0) = b \neq 0$ in general. (if $b = 0$ then the translation is both affine and linear). Anyhow, affine transformations should be familiar to you: $y = mx + b$ is an affine transformation on \mathbb{R} .

Proposition 8.8.8. translations preserve geometry

Suppose $T_b : \mathbb{R}^n \rightarrow \mathbb{R}^n$ is a translation then

1. If $\angle(xyz)$ denotes the angle formed by line segments $\bar{x}y, \bar{y}z$ which have endpoints x, y and y, z respectively then $\angle(T_b(x)T_b(y)T_b(z)) = \angle(xyz)$
2. The distance from x to y is the equal to the distance from $T_b(x)$ to $T_b(y)$.

Proof: I'll begin with (2.) since it's easy:

$$d(T_b(x), T_b(y)) = \|T_b(y) - T_b(x)\| = \|y + b - (x + b)\| = \|y - x\| = d(x, y).$$

Next, the angle $\angle(xyz)$ is the angle between $x - y$ and $z - y$. Likewise the angle $\angle T_b(x)T_b(y)T_b(z)$ is the angle between $T_b(x) - T_b(y)$ and $T_b(z) - T_b(y)$. But, these are the same vectors since $T_b(x) - T_b(y) = x + b - (y + b) = x - y$ and $T_b(z) - T_b(y) = z + b - (y + b) = z - y$. \square

Definition 8.8.9.

Suppose $T(x) = Ax + b$ where $A \in SO(n)$ and $b \in \mathbb{R}^n$ for all $x \in \mathbb{R}^n$ then we say T is a **rigid motion**.

In high-school geometry you studied the concept of *congruence*. Two objects were congruent if they had the same size and shape. From the viewpoint of analytic geometry we can say two objects are congruent iff one is the image of the other with respect to some rigid motion. We leave further discussion of such matters to the modern geometry course where you study these concepts in depth.

Remark 8.8.10.

In Chapter 6 of my *Mathematical Models in Physics* notes I describe how Euclidean geometry is implicit and foundational in classical Newtonian Mechanics. The concept of a rigid motion is used to define what is meant by an *inertial frame*. I have these notes posted on my website, ask if your interested. Chapter 7 of the same notes describes how Special Relativity has hyperbolic geometry as its core. The dot-product is replaced with a Minkowski-product which yields all manner of curious results like time-dilation, length contraction, and the constant speed of light. If your interested in hearing a lecture or two on the geometry of Special Relativity please ask and I'll try to find a time and a place.

8.9 eigenvectors and orthogonality

We can apply the Gram-Schmidt process to orthogonalize the set of e-vectors. If the resulting set of orthogonal vectors is still an eigenbasis then we can prove the matrix formed from e-vectors is an orthogonal matrix.

Proposition 8.9.1.

If $A \in \mathbb{R}^{n \times n}$ has e-values $\lambda_1, \lambda_2, \dots, \lambda_n$ with orthonormal e-vectors v_1, v_2, \dots, v_n and if we define $V = [v_1|v_2|\dots|v_n]$ then $V^{-1} = V^T$ and $D = V^T A V$ where D is a diagonal matrix with the eigenvalues down the diagonal: $D = [\lambda_1 e_1 | \lambda_2 e_2 | \dots | \lambda_n e_n]$.

Proof: Orthonormality implies $v_i^T v_j = \delta_{ij}$. Observe that

$$V^T V = \begin{bmatrix} \frac{v_1^T}{v_1^T} \\ \frac{v_2^T}{v_2^T} \\ \vdots \\ \frac{v_n^T}{v_n^T} \end{bmatrix} [v_1|v_2|\dots|v_n] = \begin{bmatrix} v_1^T v_1 & v_1^T v_2 & \cdots & v_1^T v_n \\ v_2^T v_1 & v_2^T v_2 & \cdots & v_2^T v_n \\ \vdots & \vdots & \cdots & \vdots \\ v_n^T v_1 & v_n^T v_2 & \cdots & v_n^T v_n \end{bmatrix} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix}.$$

Thus $V^{-1} = V^T$. The proposition follows from Proposition 7.5.2. \square

This is great news. We now have hope of finding the diagonalization of a matrix without going to the trouble of inverting the e-vector matrix. Notice that there is no guarantee that we can find n -orthonormal e-vectors. Even in the case we have n -linearly independent e-vectors it could happen that when we do the Gram-Schmidt process the resulting vectors are not e-vectors. That said, there is one important, and common, type of example where we are in fact guaranteed the existence of an orthonormal eigenbases for A .

Theorem 8.9.2.

A matrix $A \in \mathbb{R}^{n \times n}$ is symmetric iff there exists an orthonormal eigenbasis for A .

Proof: I'll prove the reverse implication in these notes. Your text has a complete proof of the forward implication in Appendix C, it's very neat, but we don't have that much time. Assume there exists an orthonormal eigenbasis $\{v_1, v_2, \dots, v_n\}$ for A . Let $V = [v_1|v_2|\dots|v_n]$ and use Proposition 8.9.1, $V^T A V = D$ where D is a diagonal matrix with the e-values down the diagonal. Clearly $D^T = D$. Transposing the equation yields $(V^T A V)^T = D$. Use the socks-shoes property for transpose to see $(V^T A V)^T = V^T A^T (V^T)^T = V^T A^T V$. We find that $V^T A^T V = V^T A V$. Multiply on the left by V and on the right by V^T and we find $A^T = A$ thus A is symmetric. \square .

This theorem is a useful bit of trivia to know. But, be careful not to overstate the result. This theorem does not state that all diagonalizable matrices are symmetric.

Example 8.9.3. In Example 7.2.13 we found the e -values and e -vectors of $A = \begin{bmatrix} 0 & 0 & -4 \\ 2 & 4 & 2 \\ 2 & 0 & 6 \end{bmatrix}$ were $\lambda_1 = \lambda_2 = 4$ and $\lambda_3 = 2$ with e -vectors

$$u_1 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad u_2 = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \quad u_3 = \begin{bmatrix} -2 \\ 1 \\ 1 \end{bmatrix}$$

We argued in Example 7.4.4 that $\{u_1, u_2, u_3\}$ is an eigenbasis. In view of the Theorem above we know there is no way to perform the Gram-Schmidt process and get an orthonormal set of e -vectors for A . We could orthonormalize the basis, but it would not result in a set of e -vectors. We can be certain of this since A is not symmetric. I invite you to try Gram-Schmidt and see how the process spoils the e -values. The principle calculational observation is simply that when you add e -vectors with different e -values there is no reason to expect the sum is again an e -vector. There is an exception to my last observation, what is it?

Example 8.9.4. Let $A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 2 \\ 0 & 2 & 1 \end{bmatrix}$. Observe that $\det(A - \lambda I) = -\lambda(\lambda + 1)(\lambda - 3)$ thus $\lambda_1 = 0, \lambda_2 = -1, \lambda_3 = 3$. We can calculate orthonormal e -vectors of $v_1 = [1, 0, 0]^T$, $v_2 = \frac{1}{\sqrt{2}}[0, 1, -1]^T$ and $v_3 = \frac{1}{\sqrt{2}}[0, 1, 1]^T$. I invite the reader to check the validity of the following equation:

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{2}} \\ 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 2 \\ 0 & 2 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 0 & \frac{-1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 3 \end{bmatrix}$$

It's really neat that to find the inverse of a matrix of orthonormal e -vectors we need only take the

transpose; note $\begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{2}} \\ 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 0 & \frac{-1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$.

8.10 conic sections and quadric surfaces

Some of you have taken calculus III others have not, but most of you still have much to learn about level curves and surfaces. Let me give two examples to get us started:

$$x^2 + y^2 = 4 \quad \text{level curve; generally has form } f(x, y) = k$$

$$x^2 + 4y^2 + z^2 = 1 \quad \text{level surface; generally has form } F(x, y, z) = k$$

Alternatively, some special surfaces can be written as a graph. The top half of the ellipsoid $F(x, y, z) = x^2 + 4y^2 + z^2 = 1$ is the *graph*(f) where $f(x, y) = \sqrt{1 - x^2 - 4y^2}$ and $\text{graph}(f) = \{x, y, f(x, y) \mid (x, y) \in \text{dom}(f)\}$. Of course there is a great variety of examples to offer here and I only intend to touch on a few standard examples in this section. Our goal is to see what linear algebra has to say about conic sections and quadric surfaces.

8.10.1 quadratic forms and their matrix

Definition 8.10.1.

Generally, a **quadratic form** Q is a function $Q : \mathbb{R}^n \rightarrow \mathbb{R}$ whose formula can be written $Q(\vec{x}) = \vec{x}^T A \vec{x}$ for all $\vec{x} \in \mathbb{R}^n$ where $A \in \mathbb{R}^{n \times n}$ such that $A^T = A$. In particular, if $\vec{x} = (x, y)$ and $A = \begin{bmatrix} a & b \\ b & c \end{bmatrix}$ then

$$Q(\vec{x}) = \vec{x}^T A \vec{x} = ax^2 + bxy + byx + cy^2 = ax^2 + 2bxy + y^2.$$

The $n = 3$ case is similar, denote $A = [A_{ij}]$ and $\vec{x} = (x, y, z)$ so that

$$Q(\vec{x}) = \vec{x}^T A \vec{x} = A_{11}x^2 + 2A_{12}xy + 2A_{13}xz + A_{22}y^2 + 2A_{23}yz + A_{33}z^2.$$

Generally, if $[A_{ij}] \in \mathbb{R}^{n \times n}$ and $\vec{x} = [x_i]^T$ then the associated quadratic form is

$$Q(\vec{x}) = \vec{x}^T A \vec{x} = \sum_{i,j} A_{ij} x_i x_j = \sum_{i=1}^n A_{ii} x_i^2 + \sum_{i < j} 2A_{ij} x_i x_j.$$

In case you wondering, yes you could write a given quadratic form with a different matrix which is not symmetric, but we will find it convenient to insist that our matrix is symmetric since that choice is always possible for a given quadratic form.

Also, you may recall (from the future) I said a **bilinear form** was a mapping from $V \times V \rightarrow \mathbb{R}$ which is linear in each slot. For example, an inner-product as defined in Definition 8.13.1 is a symmetric, positive definite bilinear form. When we discussed $\langle x, y \rangle$ we allowed $x \neq y$, in

contrast a quadratic form is more like $\langle x, x \rangle$. Of course the dot-product is also an inner product and we can write a given quadratic form in terms of a dot-product:

$$\vec{x}^T A \vec{x} = \vec{x} \cdot (A\vec{x}) = (A\vec{x}) \cdot \vec{x} = \vec{x}^T A^T \vec{x}$$

Some texts actually use the middle equality above to define a symmetric matrix.

Example 8.10.2.

$$2x^2 + 2xy + 2y^2 = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Example 8.10.3.

$$2x^2 + 2xy + 3xz - 2y^2 - z^2 = \begin{bmatrix} x & y & z \end{bmatrix} \begin{bmatrix} 2 & 1 & 3/2 \\ 1 & -2 & 0 \\ 3/2 & 0 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

Proposition 8.10.4.

The values of a quadratic form on $\mathbb{R}^n - \{0\}$ is completely determined by it's values on the $(n-1)$ -sphere $S_{n-1} = \{\vec{x} \in \mathbb{R}^n \mid \|\vec{x}\| = 1\}$. In particular, $Q(\vec{x}) = \|\vec{x}\|^2 Q(\hat{x})$ where $\hat{x} = \frac{1}{\|\vec{x}\|} \vec{x}$.

Proof: Let $Q(\vec{x}) = \vec{x}^T A \vec{x}$. Notice that we can write any nonzero vector as the product of its magnitude $\|\vec{x}\|$ and its direction $\hat{x} = \frac{1}{\|\vec{x}\|} \vec{x}$,

$$Q(\vec{x}) = Q(\|\vec{x}\| \hat{x}) = (\|\vec{x}\| \hat{x})^T A \|\vec{x}\| \hat{x} = \|\vec{x}\|^2 \hat{x}^T A \hat{x} = \|\vec{x}\|^2 Q(\hat{x}).$$

Therefore $Q(\vec{x})$ is simply proportional to $Q(\hat{x})$ with proportionality constant $\|\vec{x}\|^2$. \square

The proposition above is very interesting. It says that if we know how Q works on unit-vectors then we can extrapolate its action on the remainder of \mathbb{R}^n . If $f : S \rightarrow \mathbb{R}$ then we could say $f(S) > 0$ iff $f(s) > 0$ for all $s \in S$. Likewise, $f(S) < 0$ iff $f(s) < 0$ for all $s \in S$. The proposition below follows from the proposition above since $\|\vec{x}\|^2$ ranges over all nonzero positive real numbers in the equations above.

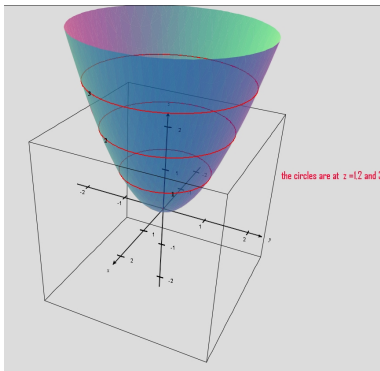
Proposition 8.10.5.

If Q is a quadratic form on \mathbb{R}^n and we denote $\mathbb{R}_*^n = \mathbb{R}^n - \{0\}$

- 1.(negative definite) $Q(\mathbb{R}_*^n) < 0$ iff $Q(S_{n-1}) < 0$
- 2.(positive definite) $Q(\mathbb{R}_*^n) > 0$ iff $Q(S_{n-1}) > 0$
- 3.(non-definite) $Q(\mathbb{R}_*^n) = \mathbb{R} - \{0\}$ iff $Q(S_{n-1})$ has both positive and negative values.

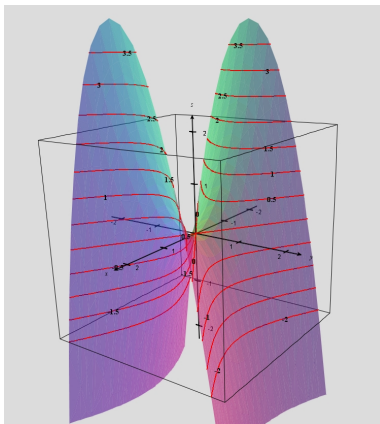
Before I get too carried away with the theory let's look at a couple examples.

Example 8.10.6. Consider the quadric form $Q(x, y) = x^2 + y^2$. You can check for yourself that $z = Q(x, y)$ is a cone and Q has positive outputs for all inputs except $(0, 0)$. Notice that $Q(v) = \|v\|^2$ so it is clear that $Q(S_1) = 1$. We find agreement with the preceding proposition. Next, think about the application of $Q(x, y)$ to level curves; $x^2 + y^2 = k$ is simply a circle of radius \sqrt{k} or just the origin. Here's a graph of $z = Q(x, y)$:



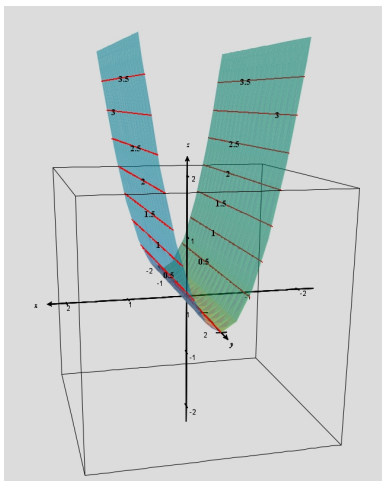
Notice that $Q(0, 0) = 0$ is the absolute minimum for Q . Finally, let's take a moment to write $Q(x, y) = [x, y] \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$ in this case the matrix is diagonal and we note that the e-values are $\lambda_1 = \lambda_2 = 1$.

Example 8.10.7. Consider the quadric form $Q(x, y) = x^2 - 2y^2$. You can check for yourself that $z = Q(x, y)$ is a hyperboloid and Q has non-definite outputs since sometimes the x^2 term dominates whereas other points have $-2y^2$ as the dominant term. Notice that $Q(1, 0) = 1$ whereas $Q(0, 1) = -2$ hence we find $Q(S_1)$ contains both positive and negative values and consequently we find agreement with the preceding proposition. Next, think about the application of $Q(x, y)$ to level curves; $x^2 - 2y^2 = k$ yields either hyperbolas which open vertically ($k > 0$) or horizontally ($k < 0$) or a pair of lines $y = \pm \frac{x}{2}$ in the $k = 0$ case. Here's a graph of $z = Q(x, y)$:



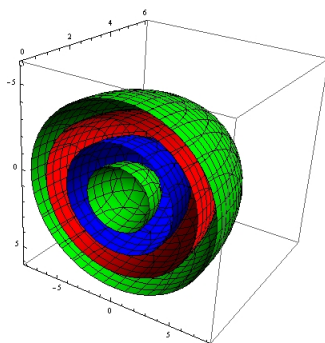
The origin is a **saddle point**. Finally, let's take a moment to write $Q(x, y) = [x, y] \begin{bmatrix} 1 & 0 \\ 0 & -2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$ in this case the matrix is diagonal and we note that the e-values are $\lambda_1 = 1$ and $\lambda_2 = -2$.

Example 8.10.8. Consider the quadric form $Q(x, y) = 3x^2$. You can check for yourself that $z = Q(x, y)$ is parabola-shaped trough along the y -axis. In this case Q has positive outputs for all inputs except $(0, y)$, we would call this form **positive semi-definite**. A short calculation reveals that $Q(S_1) = [0, 3]$ thus we again find agreement with the preceding proposition (case 3). Next, think about the application of $Q(x, y)$ to level curves; $3x^2 = k$ is a pair of vertical lines: $x = \pm\sqrt{k/3}$ or just the y -axis. Here's a graph of $z = Q(x, y)$:



Finally, let's take a moment to write $Q(x, y) = [x, y] \begin{bmatrix} 3 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$ in this case the matrix is diagonal and we note that the e-values are $\lambda_1 = 3$ and $\lambda_2 = 0$.

Example 8.10.9. Consider the quadric form $Q(x, y, z) = x^2 + 2y^2 + 3z^2$. Think about the application of $Q(x, y, z)$ to level surfaces; $x^2 + 2y^2 + 3z^2 = k$ is an ellipsoid. I can't graph a function of three variables, however, we can look at level surfaces of the function. I use Mathematica to plot several below:



Finally, let's take a moment to write $Q(x, y, z) = [x, y, z] \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$ in this case the matrix is diagonal and we note that the e-values are $\lambda_1 = 1$ and $\lambda_2 = 2$ and $\lambda_3 = 3$.

The examples given thus far are the simplest cases. We don't really need linear algebra to understand them. In contrast, e-vectors and e-values will prove a useful tool to unravel the later examples.

Proposition 8.10.10.

If Q is a quadratic form on \mathbb{R}^n with matrix A and e-values $\lambda_1, \lambda_2, \dots, \lambda_n$ with orthonormal e-vectors v_1, v_2, \dots, v_n then

$$Q(v_i) = \lambda_i^2$$

for $i = 1, 2, \dots, n$. Moreover, if $P = [v_1 | v_2 | \dots | v_n]$ then

$$Q(\vec{x}) = (P^T \vec{x})^T P^T A P P^T \vec{x} = \lambda_1 y_1^2 + \lambda_2 y_2^2 + \dots + \lambda_n y_n^2$$

where we defined $\vec{y} = P^T \vec{x}$.

Let me restate the proposition above in simple terms: we can transform a given quadratic form to a diagonal form by finding orthonormalized e-vectors and performing the appropriate coordinate transformation. Since P is formed from orthonormal e-vectors we know that P will be either a rotation or reflection. This proposition says we can remove "cross-terms" by transforming the quadratic forms with an appropriate rotation.

Example 8.10.11. Consider the quadric form $Q(x, y) = 2x^2 + 2xy + 2y^2$. It's not immediately obvious (to me) what the level curves $Q(x, y) = k$ look like. We'll make use of the preceding proposition to understand those graphs. Notice $Q(x, y) = [x, y] \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$. Denote the matrix of the form by A and calculate the e-values/vectors:

$$\det(A - \lambda I) = \det \begin{bmatrix} 2 - \lambda & 1 \\ 1 & 2 - \lambda \end{bmatrix} = (\lambda - 2)^2 - 1 = \lambda^2 - 4\lambda + 3 = (\lambda - 1)(\lambda - 3) = 0$$

Therefore, the e-values are $\lambda_1 = 1$ and $\lambda_2 = 3$.

$$(A - I)\vec{u}_1 = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \vec{u}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

I just solved $u + v = 0$ to give $v = -u$ choose $u = 1$ then normalize to get the vector above. Next,

$$(A - 3I)\vec{u}_2 = \begin{bmatrix} -1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \vec{u}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

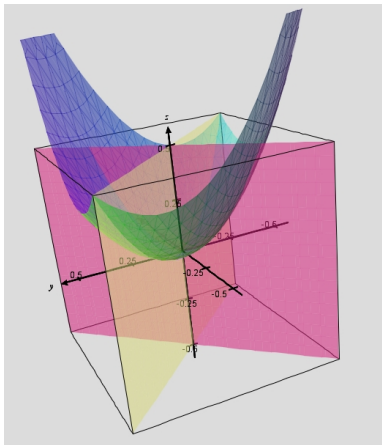
I just solved $u - v = 0$ to give $v = u$ choose $u = 1$ then normalize to get the vector above. Let $P = [\vec{u}_1 | \vec{u}_2]$ and introduce new coordinates $\vec{y} = [\bar{x}, \bar{y}]^T$ defined by $\vec{y} = P^T \vec{x}$. Note these can be inverted by multiplication by P to give $\vec{x} = P\vec{y}$. Observe that

$$P = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \Rightarrow \begin{array}{l} x = \frac{1}{2}(\bar{x} + \bar{y}) \\ y = \frac{1}{2}(-\bar{x} + \bar{y}) \end{array} \quad \text{or} \quad \begin{array}{l} \bar{x} = \frac{1}{2}(x - y) \\ \bar{y} = \frac{1}{2}(x + y) \end{array}$$

The proposition preceding this example shows that substitution of the formulas above into Q yield¹²:

$$\tilde{Q}(\bar{x}, \bar{y}) = \bar{x}^2 + 3\bar{y}^2$$

It is clear that in the barred coordinate system the level curve $Q(x, y) = k$ is an ellipse. If we draw the barred coordinate system superposed over the xy -coordinate system then you'll see that the graph of $Q(x, y) = 2x^2 + 2xy + 2y^2 = k$ is an ellipse rotated by 45 degrees. Or, if you like, we can plot $z = Q(x, y)$:



Example 8.10.12. Consider the quadric form $Q(x, y) = x^2 + 2xy + y^2$. It's not immediately obvious (to me) what the level curves $Q(x, y) = k$ look like. We'll make use of the preceding proposition to understand those graphs. Notice $Q(x, y) = [x, y] \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$. Denote the matrix of the form by A and calculate the e -values/vectors:

$$\det(A - \lambda I) = \det \begin{bmatrix} 1 - \lambda & 1 \\ 1 & 1 - \lambda \end{bmatrix} = (\lambda - 1)^2 - 1 = \lambda^2 - 2\lambda = \lambda(\lambda - 2) = 0$$

Therefore, the e -values are $\lambda_1 = 0$ and $\lambda_2 = 2$.

$$(A - 0I)\vec{u}_1 = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \vec{u}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

I just solved $u + v = 0$ to give $v = -u$ choose $u = 1$ then normalize to get the vector above. Next,

$$(A - 2I)\vec{u}_2 = \begin{bmatrix} -1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \vec{u}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

I just solved $u - v = 0$ to give $v = u$ choose $u = 1$ then normalize to get the vector above. Let $P = [\vec{u}_1 | \vec{u}_2]$ and introduce new coordinates $\bar{y} = [\bar{x}, \bar{y}]^T$ defined by $\bar{y} = P^T \vec{x}$. Note these can be inverted by multiplication by P to give $\vec{x} = P\bar{y}$. Observe that

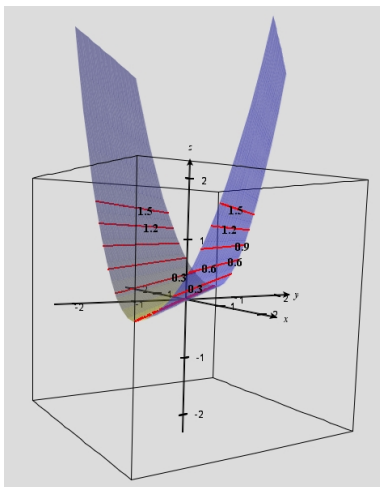
$$P = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \Rightarrow \begin{array}{l} x = \frac{1}{2}(\bar{x} + \bar{y}) \\ y = \frac{1}{2}(-\bar{x} + \bar{y}) \end{array} \quad \text{or} \quad \begin{array}{l} \bar{x} = \frac{1}{2}(x - y) \\ \bar{y} = \frac{1}{2}(x + y) \end{array}$$

¹²technically $\tilde{Q}(\bar{x}, \bar{y})$ is $Q(x(\bar{x}, \bar{y}), y(\bar{x}, \bar{y}))$

The proposition preceding this example shows that substitution of the formulas above into Q yield:

$$\tilde{Q}(\bar{x}, \bar{y}) = 2\bar{y}^2$$

It is clear that in the barred coordinate system the level curve $Q(x, y) = k$ is a pair of parallel lines. If we draw the barred coordinate system superposed over the xy -coordinate system then you'll see that the graph of $Q(x, y) = x^2 + 2xy + y^2 = k$ is a line with slope -1 . Indeed, with a little algebraic insight we could have anticipated this result since $Q(x, y) = (x+y)^2$ so $Q(x, y) = k$ implies $x + y = \sqrt{k}$ thus $y = \sqrt{k} - x$. Here's a plot which again verifies what we've already found:



Example 8.10.13. Consider the quadric form $Q(x, y) = 4xy$. It's not immediately obvious (to me) what the level curves $Q(x, y) = k$ look like. We'll make use of the preceding proposition to understand those graphs. Notice $Q(x, y) = [x, y] \begin{bmatrix} 0 & 2 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$. Denote the matrix of the form by A and calculate the e-values/vectors:

$$\det(A - \lambda I) = \det \begin{bmatrix} -\lambda & 2 \\ 2 & -\lambda \end{bmatrix} = \lambda^2 - 4 = (\lambda + 2)(\lambda - 2) = 0$$

Therefore, the e-values are $\lambda_1 = -2$ and $\lambda_2 = 2$.

$$(A + 2I)\vec{u}_1 = \begin{bmatrix} 2 & 2 \\ 2 & 2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \vec{u}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

I just solved $u + v = 0$ to give $v = -u$ choose $u = 1$ then normalize to get the vector above. Next,

$$(A - 2I)\vec{u}_2 = \begin{bmatrix} -2 & 2 \\ 2 & -2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \vec{u}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

I just solved $u - v = 0$ to give $v = u$ choose $u = 1$ then normalize to get the vector above. Let $P = [\vec{u}_1 | \vec{u}_2]$ and introduce new coordinates $\vec{y} = [\bar{x}, \bar{y}]^T$ defined by $\vec{y} = P^T \vec{x}$. Note these can be

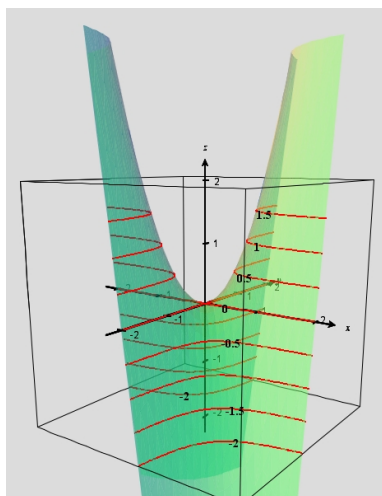
inverted by multiplication by P to give $\vec{x} = P\vec{y}$. Observe that

$$P = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \Rightarrow \begin{aligned} x &= \frac{1}{2}(\bar{x} + \bar{y}) \\ y &= \frac{1}{2}(-\bar{x} + \bar{y}) \end{aligned} \quad \text{or} \quad \begin{aligned} \bar{x} &= \frac{1}{2}(x - y) \\ \bar{y} &= \frac{1}{2}(x + y) \end{aligned}$$

The proposition preceding this example shows that substitution of the formulas above into Q yield:

$$\tilde{Q}(\bar{x}, \bar{y}) = -2\bar{x}^2 + 2\bar{y}^2$$

It is clear that in the barred coordinate system the level curve $Q(x, y) = k$ is a hyperbola. If we draw the barred coordinate system superposed over the xy -coordinate system then you'll see that the graph of $Q(x, y) = 4xy = k$ is a hyperbola rotated by 45 degrees. The graph $z = 4xy$ is thus a hyperbolic paraboloid:



The fascinating thing about the mathematics here is that if you don't want to graph $z = Q(x, y)$, but you do want to know the general shape then you can determine which type of quadraic surface you're dealing with by simply calculating the eigenvalues of the form.

Remark 8.10.14.

I made the preceding triple of examples all involved the same rotation. This is purely for my lecturing convenience. In practice the rotation could be by all sorts of angles. In addition, you might notice that a different ordering of the e-values would result in a redefinition of the barred coordinates. ¹³

We ought to do at least one 3-dimensional example.

Example 8.10.15. Consider the quadric form Q defined below:

$$Q(x, y, z) = [x, y, z] \begin{bmatrix} 6 & -2 & 0 \\ -2 & 6 & 0 \\ 0 & 0 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

Denote the matrix of the form by A and calculate the e -values/vectors:

$$\begin{aligned} \det(A - \lambda I) &= \det \begin{bmatrix} 6 - \lambda & -2 & 0 \\ -2 & 6 - \lambda & 0 \\ 0 & 0 & 5 - \lambda \end{bmatrix} \\ &= [(\lambda - 6)^2 - 4](5 - \lambda) \\ &= (5 - \lambda)[\lambda^2 - 12\lambda + 32](5 - \lambda) \\ &= (\lambda - 4)(\lambda - 8)(5 - \lambda) \end{aligned}$$

Therefore, the e -values are $\lambda_1 = 4$, $\lambda_2 = 8$ and $\lambda_3 = 5$. After some calculation we find the following orthonormal e -vectors for A :

$$\vec{u}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \quad \vec{u}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix} \quad \vec{u}_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

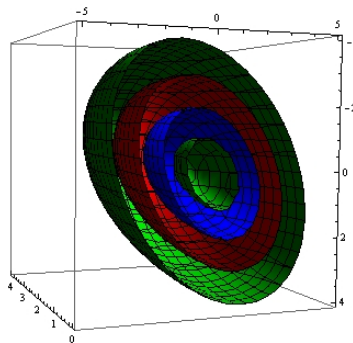
Let $P = [\vec{u}_1 | \vec{u}_2 | \vec{u}_3]$ and introduce new coordinates $\vec{y} = [\bar{x}, \bar{y}, \bar{z}]^T$ defined by $\vec{y} = P^T \vec{x}$. Note these can be inverted by multiplication by P to give $\vec{x} = P\vec{y}$. Observe that

$$P = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 & 0 \\ -1 & 1 & 0 \\ 0 & 0 & \sqrt{2} \end{bmatrix} \Rightarrow \begin{array}{lcl} x & = & \frac{1}{2}(\bar{x} + \bar{y}) \\ y & = & \frac{1}{2}(-\bar{x} + \bar{y}) \\ z & = & \bar{z} \end{array} \quad \text{or} \quad \begin{array}{lcl} \bar{x} & = & \frac{1}{2}(x - y) \\ \bar{y} & = & \frac{1}{2}(x + y) \\ \bar{z} & = & z \end{array}$$

The proposition preceding this example shows that substitution of the formulas above into Q yield:

$$\tilde{Q}(\bar{x}, \bar{y}, \bar{z}) = 4\bar{x}^2 + 8\bar{y}^2 + 5\bar{z}^2$$

It is clear that in the barred coordinate system the level surface $Q(x, y, z) = k$ is an ellipsoid. If we draw the barred coordinate system superposed over the xyz -coordinate system then you'll see that the graph of $Q(x, y, z) = k$ is an ellipsoid rotated by 45 degrees around the z -axis. Plotted below are a few representative ellipsoids:



Remark 8.10.16.

If you would like to read more about conic sections or quadric surfaces and their connection to e-values/vectors I recommend sections 9.6 and 9.7 of Anton's text. I have yet to add examples on how to include translations in the analysis. It's not much more trouble but I decided it would just be an unnecessary complication this semester. Also, section 7.1, 7.2 and 7.3 in Lay's text show a bit more about how to use this math to solve concrete applied problems. You might also take a look in Strang's text, his discussion of tests for positive-definite matrices is much more complete than I will give here.

8.10.2 summary of quadratic form analysis

There is a connection between the shape of level curves $Q(x_1, x_2, \dots, x_n) = k$ and the graph $x_{n+1} = f(x_1, x_2, \dots, x_n)$ of f . I'll discuss $n = 2$ but these comments equally well apply to $w = f(x, y, z)$ or higher dimensional examples. Consider a critical point (a, b) for $f(x, y)$ then the Taylor expansion about (a, b) has the form

$$f(a + h, b + k) = f(a, b) + Q(h, k)$$

where $Q(h, k) = \frac{1}{2}h^2 f_{xx}(a, b) + hk f_{xy}(a, b) + \frac{1}{2}k^2 f_{yy}(a, b) = [h, k][Q](h, k)$. Since $[Q]^T = [Q]$ we can find orthonormal e-vectors \vec{u}_1, \vec{u}_2 for $[Q]$ with e-values λ_1 and λ_2 respectively. Using $U = [\vec{u}_1 | \vec{u}_2]$ we can introduce rotated coordinates $(\bar{h}, \bar{k}) = U(h, k)$. These will give

$$Q(\bar{h}, \bar{k}) = \lambda_1 \bar{h}^2 + \lambda_2 \bar{k}^2$$

Clearly if $\lambda_1 > 0$ and $\lambda_2 > 0$ then $f(a, b)$ yields the local minimum whereas if $\lambda_1 < 0$ and $\lambda_2 < 0$ then $f(a, b)$ yields the local maximum. Edwards discusses these matters on pgs. 148-153. In short, supposing $f \approx f(p) + Q$, if all the e-values of Q are positive then f has a local minimum of $f(p)$ at p whereas if all the e-values of Q are negative then f reaches a local maximum of $f(p)$ at p . Otherwise Q has both positive and negative e-values and we say Q is non-definite and the function has a saddle point. If all the e-values of Q are positive then Q is said to be **positive-definite** whereas if all the e-values of Q are negative then Q is said to be **negative-definite**. Edwards gives a few nice tests for ascertaining if a matrix is positive definite without explicit computation of e-values. Finally, if one of the e-values is zero then the graph will be like a trough.

Remark 8.10.17. summary of the summary.

In short, the behaviour of a quadratic form $Q(x) = x^T A x$ is governed by its spectrum $\{\lambda_1, \lambda_2, \dots, \lambda_k\}$. Moreover, the form can be written as $Q(y) = \lambda_1 y_1^2 + \lambda_2 y_2^2 + \dots + \lambda_k y_k^2$ by choosing the coordinate system which is built from the orthonormal eigenbasis of $\text{col}(A)$. In this coordinate system questions of optimization become trivial (see section 7.3 of Lay for applied problems)

8.11 Taylor series for functions of two or more variables

It turns out that linear algebra and e-vectors can give us great insight into locating local extrema for a function of several variables. To summarize, we can calculate the multivariate Taylor series and we'll find that the quadratic terms correspond to a *quadratic form*. In fact, each quadratic form has a symmetric matrix representative. We know that symmetric matrices are diagonalizable hence the e-values of a symmetric matrix will be real. Moreover, the eigenvalues tell you what the min/max value of the function is at a critical point (usually). This is the n -dimensional generalization of the 2nd-derivative test from calculus. I'll only study the $n = 2$ and $n = 3$ case in this course. If you'd like to see these claims explained in more depth feel free to join us in math 331 in the 2011 + $2k - 1$ for $k \in \mathbb{N}$ spring semester.

Our goal here is to find an analogue for Taylor's Theorem for function from \mathbb{R}^n to \mathbb{R} . Recall that if $g : U \subseteq \mathbb{R} \rightarrow \mathbb{R}$ is *smooth* at $a \in \mathbb{R}$ then we can compute as many derivatives as we wish, moreover we can generate the Taylor's series for g centered at a :

$$g(a+h) = g(a) + g'(a)h + \frac{1}{2}g''(a)h^2 + \frac{1}{3!}g'''(a)h^3 + \cdots = \sum_{n=0}^{\infty} \frac{g^{(n)}(a)}{n!} h^n$$

The equation above assumes that g is analytic at a . In other words, the function actually matches it's Taylor series near a . This concept can be made rigorous by discussing the remainder. If one can show the remainder goes to zero then that proves the function is analytic. (*read p117-127 of Edwards for more on these concepts, I did cover some of that in class this semester, Theorem 6.3 is particularly interesting*).

8.11.1 deriving the two-dimensional Taylor formula

The idea is fairly simple: create a function on \mathbb{R} with which we can apply the ordinary Taylor series result. Much like our discussion of directional derivatives we compose a function of two variables with linear path in the domain. Let $f : U \subseteq \mathbb{R}^2 \rightarrow \mathbb{R}$ be smooth with smooth partial derivatives of all orders. Furthermore, let $(a, b) \in U$ and construct a line through (a, b) with direction vector (h_1, h_2) as usual:

$$\phi(t) = (a, b) + t(h_1, h_2) = (a + th_1, b + th_2)$$

for $t \in \mathbb{R}$. Note $\phi(0) = (a, b)$ and $\phi'(t) = (h_1, h_2) = \phi'(0)$. Construct $g = f \circ \phi : \mathbb{R} \rightarrow \mathbb{R}$ and differentiate, note we use the chain rule for functions of several variables in what follows:

$$\begin{aligned} g'(t) &= (f \circ \phi)'(t) = f'(\phi(t))\phi'(t) \\ &= \nabla f(\phi(t)) \cdot (h_1, h_2) \\ &= h_1 f_x(a + th_1, b + th_2) + h_2 f_y(a + th_1, b + th_2) \end{aligned}$$

Note $g'(0) = h_1 f_x(a, b) + h_2 f_y(a, b)$. Differentiate again (I omit $(\phi(t))$ dependence in the last steps),

$$\begin{aligned} g''(t) &= h_1 f'_x(a + th_1, b + th_2) + h_2 f'_y(a + th_1, b + th_2) \\ &= h_1 \nabla f_x(\phi(t)) \cdot (h_1, h_2) + h_2 \nabla f_y(\phi(t)) \cdot (h_1, h_2) \\ &= h_1^2 f_{xx} + h_1 h_2 f_{yx} + h_2 h_1 f_{xy} + h_2^2 f_{yy} \\ &= h_1^2 f_{xx} + 2h_1 h_2 f_{xy} + h_2^2 f_{yy} \end{aligned}$$

Thus, making explicit the point dependence, $g''(0) = h_1^2 f_{xx}(a, b) + 2h_1 h_2 f_{xy}(a, b) + h_2^2 f_{yy}(a, b)$. We may construct the Taylor series for g up to quadratic terms:

$$\begin{aligned} g(0+t) &= g(0) + tg'(0) + \frac{1}{2}g''(0) + \cdots \\ &= f(a, b) + t[h_1 f_x(a, b) + h_2 f_y(a, b)] + \frac{t^2}{2}[h_1^2 f_{xx}(a, b) + 2h_1 h_2 f_{xy}(a, b) + h_2^2 f_{yy}(a, b)] + \cdots \end{aligned}$$

Note that $g(t) = f(a + th_1, b + th_2)$ hence $g(1) = f(a + h_1, b + h_2)$ and consequently,

$$\begin{aligned} f(a + h_1, b + h_2) &= f(a, b) + h_1 f_x(a, b) + h_2 f_y(a, b) + \\ &\quad + \frac{1}{2} \left[h_1^2 f_{xx}(a, b) + 2h_1 h_2 f_{xy}(a, b) + h_2^2 f_{yy}(a, b) \right] + \cdots \end{aligned}$$

Omitting point dependence on the 2^{nd} derivatives,

$$\boxed{f(a + h_1, b + h_2) = f(a, b) + h_1 f_x(a, b) + h_2 f_y(a, b) + \frac{1}{2} [h_1^2 f_{xx} + 2h_1 h_2 f_{xy} + h_2^2 f_{yy}] + \cdots}$$

Sometimes we'd rather have an expansion about (x, y) . To obtain that formula simply substitute $x - a = h_1$ and $y - b = h_2$. Note that the point (a, b) is fixed in this discussion so the derivatives are not modified in this substitution,

$$\begin{aligned} f(x, y) &= f(a, b) + (x - a)f_x(a, b) + (y - b)f_y(a, b) + \\ &\quad + \frac{1}{2} \left[(x - a)^2 f_{xx}(a, b) + 2(x - a)(y - b)f_{xy}(a, b) + (y - b)^2 f_{yy}(a, b) \right] + \cdots \end{aligned}$$

At this point we ought to recognize the first three terms give the tangent plane to $z = f(x, y)$ at $(a, b, f(a, b))$. The higher order terms are nonlinear corrections to the linearization, these quadratic terms form a *quadratic form*. If we computed third, fourth or higher order terms we'd find that, using $a = a_1$ and $b = a_2$ as well as $x = x_1$ and $y = x_2$,

$$\boxed{f(x, y) = \sum_{n=0}^{\infty} \sum_{i_1=0}^n \sum_{i_2=0}^n \cdots \sum_{i_n=0}^n \frac{1}{n!} \frac{\partial^{(n)} f(a_1, a_2)}{\partial x_{i_1} \partial x_{i_2} \cdots \partial x_{i_n}} (x_{i_1} - a_{i_1})(x_{i_2} - a_{i_2}) \cdots (x_{i_n} - a_{i_n})}$$

The multivariate Taylor formula for a function of j -variables for $j > 2$ is very similar. Rather than even state the formula I will show a few examples in the subsection that follows.

8.11.2 examples

Example 8.11.1. Suppose $f(x, y) = \exp(-x^2 - y^2 + 2y - 1)$ expand f about the point $(0, 1)$:

$$f(x, y) = \exp(-x^2)\exp(-y^2 + 2y - 1) = \exp(-x^2)\exp(-(y - 1)^2)$$

expanding,

$$f(x, y) = (1 - x^2 + \cdots)(1 - (y - 1)^2 + \cdots) = 1 - x^2 - (y - 1)^2 + \cdots$$

Recenter about the point $(0, 1)$ by setting $x = h$ and $y = 1 + k$ so

$$f(h, 1 + k) = 1 - h^2 - k^2 + \cdots$$

If (h, k) is near $(0, 0)$ then the dominant terms are simply those we've written above hence the graph is like that of a quadraic surface with a pair of negative e -values. It follows that $f(0, 1)$ is a local maximum. In fact, it happens to be a global maximum for this function.

Example 8.11.2. Suppose $f(x, y) = 4 - (x - 1)^2 + (y - 2)^2 + A\exp(-(x - 1)^2 - (y - 2)^2) + 2B(x - 1)(y - 2)$ for some constants A, B . Analyze what values for A, B will make $(1, 2)$ a local maximum, minimum or neither. Expanding about $(1, 2)$ we set $x = 1 + h$ and $y = 2 + k$ in order to see clearly the local behaviour of f at $(1, 2)$,

$$\begin{aligned} f(1 + h, 2 + k) &= 4 - h^2 - k^2 + A\exp(-h^2 - k^2) + 2Bhk \\ &= 4 - h^2 - k^2 + A(1 - h^2 - k^2) + 2Bhk \cdots \\ &= 4 + A - (A + 1)h^2 + 2Bhk - (A + 1)k^2 + \cdots \end{aligned}$$

There is no nonzero linear term in the expansion at $(1, 2)$ which indicates that $f(1, 2) = 4 + A$ may be a local extremum. In this case the quadratic terms are nontrivial which means the graph of this function is well-approximated by a quadraic surface near $(1, 2)$. The quadratic form $Q(h, k) = -(A + 1)h^2 + 2Bhk - (A + 1)k^2$ has matrix

$$[Q] = \begin{bmatrix} -(A + 1) & B \\ B & -(A + 1) \end{bmatrix}.$$

The characteristic equation for Q is

$$\det([Q] - \lambda I) = \det \begin{bmatrix} -(A + 1) - \lambda & B \\ B & -(A + 1) - \lambda \end{bmatrix} = (\lambda + A + 1)^2 - B^2 = 0$$

We find solutions $\lambda_1 = -A - 1 + B$ and $\lambda_2 = -A - 1 - B$. The possibilities break down as follows:

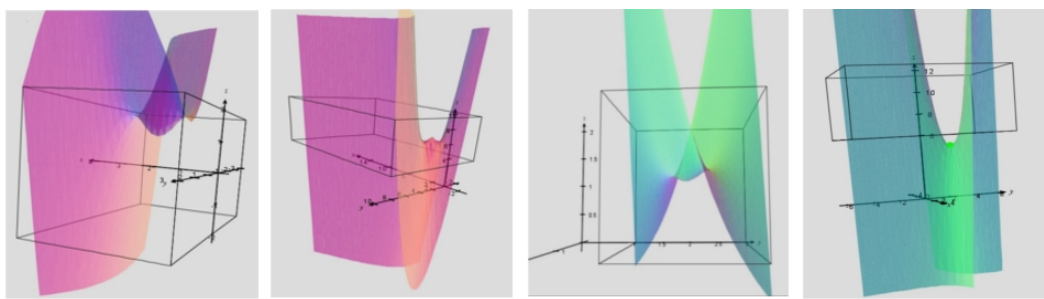
1. if $\lambda_1, \lambda_2 > 0$ then $f(1, 2)$ is local minimum.
2. if $\lambda_1, \lambda_2 < 0$ then $f(1, 2)$ is local maximum.
3. if just one of λ_1, λ_2 is zero then f is constant along one direction and min/max along another so technically it is a local extremum.

4. if $\lambda_1\lambda_2 < 0$ then $f(1,2)$ is not a local extremum, however it is a saddle point.

In particular, the following choices for A, B will match the choices above

1. Let $A = -3$ and $B = 1$ so $\lambda_1 = 3$ and $\lambda_2 = 1$;
2. Let $A = 3$ and $B = 1$ so $\lambda_1 = -3$ and $\lambda_2 = -5$
3. Let $A = -3$ and $B = -2$ so $\lambda_1 = 0$ and $\lambda_2 = 4$
4. Let $A = 1$ and $B = 3$ so $\lambda_1 = 1$ and $\lambda_2 = -5$

Here are the graphs of the cases above, note the analysis for case 3 is more subtle for Taylor approximations as opposed to simple quadraic surfaces. In this example, case 3 was also a local minimum. In contrast, in Example 8.10.12 the graph was like a trough. The behaviour of f away from the critical point includes higher order terms whose influence turns the trough into a local minimum.



Example 8.11.3. Suppose $f(x, y) = \sin(x) \cos(y)$ to find the Taylor series centered at $(0, 0)$ we can simply multiply the one-dimensional result $\sin(x) = x - \frac{1}{3!}x^3 + \frac{1}{5!}x^5 + \dots$ and $\cos(y) = 1 - \frac{1}{2!}y^2 + \frac{1}{4!}y^4 + \dots$ as follows:

$$\begin{aligned} f(x, y) &= (x - \frac{1}{3!}x^3 + \frac{1}{5!}x^5 + \dots)(1 - \frac{1}{2!}y^2 + \frac{1}{4!}y^4 + \dots) \\ &= x - \frac{1}{2}xy^2 + \frac{1}{24}xy^4 - \frac{1}{6}x^3 - \frac{1}{12}x^3y^2 + \dots \\ &= x + \dots \end{aligned}$$

The origin $(0, 0)$ is a critical point since $f_x(0, 0) = 0$ and $f_y(0, 0) = 0$, however, this particular critical point escapes the analysis via the quadratic form term since $Q = 0$ in the Taylor series for this function at $(0, 0)$. This is analogous to the inconclusive case of the 2nd derivative test in calculus III.

Example 8.11.4. Suppose $f(x, y, z) = xyz$. Calculate the multivariate Taylor expansion about the point $(1, 2, 3)$. I'll actually calculate this one via differentiation, I have used tricks and/or calculus II results to shortcut any differentiation in the previous examples. Calculate first derivatives

$$f_x = yz \quad f_y = xz \quad f_z = xy,$$

and second derivatives,

$$\begin{array}{lll} f_{xx} = 0 & f_{xy} = z & f_{xz} = y \\ f_{yx} = z & f_{yy} = 0 & f_{yz} = x \\ f_{zx} = y & f_{zy} = x & f_{zz} = 0, \end{array}$$

and the nonzero third derivatives,

$$f_{xyz} = f_{yzx} = f_{zxy} = f_{zyx} = f_{yxz} = f_{xzy} = 1.$$

It follows,

$$\begin{aligned} f(a+h, b+k, c+l) &= \\ &= f(a, b, c) + f_x(a, b, c)h + f_y(a, b, c)k + f_z(a, b, c)l + \\ &\quad \frac{1}{2}(f_{xx}hh + f_{xy}hk + f_{xz}hl + f_{yx}kh + f_{yy}kk + f_{yz}kl + f_{zx}lh + f_{zy}lk + f_{zz}ll) + \dots \end{aligned}$$

Of course certain terms can be combined since $f_{xy} = f_{yx}$ etc... for smooth functions (we assume smooth in this section, moreover the given function here is clearly smooth). In total,

$$f(1+h, 2+k, 3+l) = 6 + 6h + 3k + 2l + \frac{1}{2}(3hk + 2hl + 3kh + kl + 2lh + lk) + \frac{1}{3!}(6)hkl$$

Of course, we could also obtain this from simple algebra:

$$f(1+h, 2+k, 3+l) = (1+h)(2+k)(3+l) = 6 + 6h + 3k + l + 3hk + 2hl + kl + hkl.$$

Remark 8.11.5.

One very interesting application of the orthogonal complement theorem is to the method of Lagrange multipliers. The problem is to maximize an objective function $f(x_1, x_2, \dots, x_n)$ with respect to a set of constraint functions $g_1(x_1, x_2, \dots, x_n) = 0$, $g_2(x_1, x_2, \dots, x_n) = 0$ and $g_k(x_1, x_2, \dots, x_n) = 0$. One can argue that extreme values for f must satisfy

$$\nabla f = \lambda_1 \nabla g_1 + \lambda_2 \nabla g_2 + \dots + \lambda_k \nabla g_k$$

for a particular set of Lagrange multipliers $\lambda_1, \lambda_2, \dots, \lambda_k$. The crucial step in the analysis relies on the orthogonal decomposition theorem. It is the fact that forces the gradient of the objective function to reside in the span of the gradients of the constraints. See my Advanced Calculus 2010 notes Chapter 8, or consult many advanced calculus texts.

8.12 inertia tensor, an application of quadratic forms

We can use quadratic forms to elegantly state a number of interesting quantities in classical mechanics. For example, the translational kinetic energy of a mass m with velocity v is

$$T_{trans}(v) = \frac{m}{2} v^T v = [v_1, v_2, v_3] \begin{bmatrix} m/2 & 0 & 0 \\ 0 & m/2 & 0 \\ 0 & 0 & m/2 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix}.$$

On the other hand, the rotational kinetic energy of an object with moment of inertia I and angular velocity ω with respect to a particular axis of rotation is

$$T_{rot}(v) = \frac{I}{2} \omega^T \omega.$$

In addition you might recall that the force F applied at radial arm r gave rise to a torque of $\tau = r \times F$ which made the angular momentum $L = I\omega$ have the time-rate of change $\tau = \frac{dL}{dt}$. In the first semester of physics this is primarily all we discuss. We are usually careful to limit the discussion to rotations which happen to occur with respect to a particular axis. But, what about other rotations? What about rotations with respect to less natural axes of rotation? How should we describe the rotational physics of a rigid body which spins around some axis which doesn't happen to line up with one of the nice examples you find in an introductory physics text?

The answer is found in extending the idea of the moment of inertia to what is called the inertia tensor I_{ij} (in this section I is not the identity). To begin I'll provide a calculation which motivates the definition for the inertia tensor.

Consider a rigid mass with density $\rho = dm/dV$ which is a function of position $r = (x_1, x_2, x_3)$. Suppose the body rotates with angular velocity ω about some axis through the origin, however it is otherwise not in motion. This means all of the energy is rotational. Suppose that dm is at r then we define $v = (\dot{x}_1, \dot{x}_2, \dot{x}_3) = dr/dt$. In this context, the velocity v of dm is also given by the cross-product with the angular velocity; $v = \omega \times r$. Using the einstein repeated summation notation the k -th component of the cross-product is nicely expressed via the Levi-Civita symbol; $(\omega \times r)_k = \epsilon_{klm} \omega_l x_m$. Therefore, $v_k = \epsilon_{klm} \omega_l x_m$. The infinitesimal kinetic energy due to this little

bit of rotating mass dm is hence

$$\begin{aligned}
 dT &= \frac{dm}{2} v_k v_k \\
 &= \frac{dm}{2} (\epsilon_{klm} \omega_l x_m) (\epsilon_{kij} \omega_i x_j) \\
 &= \frac{dm}{2} \epsilon_{klm} \epsilon_{kij} \omega_l \omega_i x_m x_j \\
 &= \frac{dm}{2} (\delta_{li} \delta_{mj} - \delta_{lj} \delta_{mi}) \omega_l \omega_i x_m x_j \\
 &= \frac{dm}{2} (\delta_{li} \delta_{mj} \omega_l \omega_i x_m x_j - \delta_{lj} \delta_{mi} \omega_l \omega_i x_m x_j) \\
 &= \omega_l \frac{dm}{2} (\delta_{li} \delta_{mj} x_m x_j - \delta_{lj} \delta_{mi} x_m x_j) \omega_i \\
 &= \omega_l \left[\frac{dm}{2} (\delta_{li} \|r\|^2 - x_l x_i) \right] \omega_i.
 \end{aligned}$$

Integrating over the mass, if we add up all the little bits of kinetic energy we obtain the total kinetic energy for this rotating body: we replace dm with $\rho(r)dV$ and the integration is over the volume of the body,

$$T = \int \omega_l \left[\frac{1}{2} (\delta_{li} \|r\|^2 - x_l x_i) \right] \omega_i \rho(r) dV$$

However, the body is rigid so the angular velocity is the same for each dm and we can pull the components of the angular velocity out of the integration¹⁴ to give:

$$T = \frac{1}{2} \omega_j \underbrace{\left[\int (\delta_{jk} \|r\|^2 - x_j x_k) \rho(r) dV \right]}_{I_{jk}} \omega_k$$

This integral defines the inertia tensor I_{jk} for the rotating body. Given the inertia tensor I_{lk} the kinetic energy is simply the value of the quadratic form below:

$$T(\omega) = \frac{1}{2} \omega^T \omega = [\omega_1, \omega_2, \omega_3] \begin{bmatrix} I_{11} & I_{12} & I_{13} \\ I_{21} & I_{22} & I_{23} \\ I_{31} & I_{32} & I_{33} \end{bmatrix} \begin{bmatrix} \omega_1 \\ \omega_2 \\ \omega_3 \end{bmatrix}.$$

The matrix above is not generally diagonal, however you can prove it is symmetric (easy). Therefore, we can find an orthonormal eigenbasis $\beta = \{u_1, u_2, u_3\}$ and if $P = [\beta]$ then it follows by orthonormality of the basis that $[I]_{\beta, \beta} = P^T [I] P$ is diagonal. The eigenvalues of the inertia tensor (the matrix $[I_{jk}]$) are called the **principle moments of inertia** and the eigenbasis $\beta = \{u_1, u_2, u_3\}$ define the **principle axes** of the body.

¹⁴I also relabelled the indices to have nicer final formula, nothing profound here

The study of the rotational dynamics flows from analyzing the equations:

$$L_i = I_{ij}\omega_j \quad \text{and} \quad \tau_i = \frac{dL_i}{dt}$$

If the initial angular velocity is in the direction of a principle axis u_1 then the motion is basically described in the same way as in the introductory physics course provided that the torque is also in the direction of u_1 . The moment of inertia is simply the first principle moment of inertia and $L = \lambda_1\omega$. However, if the torque is not in the direction of a principle axis or the initial angular velocity is not along a principle axis then the motion is more complicated since the rotational motion is connected to more than one axis of rotation. Think about a spinning top which is spinning in place. There is wobbling and other more complicated motions that are covered by the mathematics described here.

Example 8.12.1. *The inertia tensor for a cube with one corner at the origin is found to be*

$$I = \frac{2}{3}Ms^2 \begin{bmatrix} 1 & -3/8 & -3/8 \\ -3/8 & 1 & -3/8 \\ -3/8 & -3/8 & 1 \end{bmatrix}$$

Introduce $m = M/8$ to remove the fractions,

$$I = \frac{2}{3}Ms^2 \begin{bmatrix} 8 & -3 & -3 \\ -3 & 8 & -3 \\ -3 & -3 & 8 \end{bmatrix}$$

You can calculate that the e -values are $\lambda_1 = 2$ and $\lambda_2 = \lambda_3 = 11$ with principle axis in the directions

$$u_1 = \frac{1}{\sqrt{3}}(1, 1, 1), \quad u_2 = \frac{1}{\sqrt{2}}(-1, 1, 0), \quad u_3 = \frac{1}{\sqrt{2}}(-1, 0, 1).$$

The choice of u_2, u_3 is not unique. We could just as well choose any other orthonormal basis for $\text{span}\{u_2, u_3\} = W_{11}$.

Finally, a word of warning, for a particular body there may be so much symmetry that no particular eigenbasis is specified. There may be many choices of an orthonormal eigenbasis for the system. Consider a sphere. Any orthonormal basis will give a set of principle axes. Or, for a right circular cylinder the axis of the cylinder is clearly a principle axis however the other two directions are arbitrarily chosen from the plane which is the orthogonal complement of the axis. I think it's fair to say that if a body has a unique (up to ordering) set of principle axes then the shape has to be somewhat ugly. Symmetry is beauty but it implies ambiguity for the choice of certain principle axes.

8.13 inner products

We follow Chapter 6 of Anton & Rorres' *Elementary Linear Algebra*, this material is also § 7.5 of Spence, Insel & Friedberg's *Elementary Linear Algebra, a Matrix Approach*. The definition of an inner product is based on the idea of the dot product. Proposition 8.1.4 summarized the most important properties. We take these as the definition for an inner product. If you examine proofs in § 8.1 you'll notice most of what I argued was based on using these 4 simple facts for the dot-product.

WARNING: the next couple pages is dense. It's a reiteration of the main theoretical accomplishments of this chapter in the context of inner product spaces. If you need to see examples first then skip ahead as needed.

Definition 8.13.1.

Let V be a vector space over \mathbb{R} . If there is a function $\langle \cdot, \cdot \rangle: V \times V \rightarrow \mathbb{R}$ such that for all $x, y, z \in V$ and $c \in \mathbb{R}$,

1. $\langle x, y \rangle = \langle y, x \rangle$ (**symmetric**),
2. $\langle x + y, z \rangle = \langle x, z \rangle + \langle y, z \rangle$,
3. $\langle cx, y \rangle = c \langle x, y \rangle$,
4. $\langle x, x \rangle \geq 0$ and $\langle x, x \rangle = 0$ iff $x = 0$,

then we say $\langle \cdot, \cdot \rangle$ is an **inner product** on V . In this case we say V with $\langle \cdot, \cdot \rangle$ is an inner product space. Items (1.), (2.) and (3.) together allow us to call $\langle \cdot, \cdot \rangle$ a real-valued **symmetric-bilinear-form** on V . We may find it useful to use the notation $g(x, y) = \langle x, y \rangle$ for some later arguments, one should keep in mind the notation $\langle \cdot, \cdot \rangle$ is not the only choice.

Technically, items (2.) and (3.) give us "linearity in the first slot". To obtain bilinearity we need to have linearity in the second slot as well. This means $\langle x, y + z \rangle = \langle x, y \rangle + \langle x, z \rangle$ and $\langle x, cy \rangle = c \langle x, y \rangle$ for all $x, y, z \in V$ and $c \in \mathbb{R}$. Fortunately, the symmetry property will transfer the linearity to the second slot. I leave that as an exercise for the reader.

Example 8.13.2. Obviously \mathbb{R}^n together with the dot-product forms an inner product space. Moreover, the dot-product is an inner product.

Once we have an inner product for a vector space then we also have natural definitions for the length of a vector and the distance between two points.

Definition 8.13.3.

Let V be an inner product vector space with inner product $\langle \cdot, \cdot \rangle$. The **norm** or **length** of a vector is defined by $\|x\| = \sqrt{\langle x, x \rangle}$ for each $x \in V$. Likewise the **distance** between $a, b \in V$ is defined by $d(a, b) = \sqrt{\langle b - a, b - a \rangle} = \|b - a\|$ for all $a, b \in V$. We say these are the length and distance functions induced by $\langle \cdot, \cdot \rangle$. Likewise the **angle** between two nonzero vectors is defined implicitly by $\langle v, w \rangle = \|v\| \|w\| \cos(\theta)$.

As before the definition above is only logical if certain properties hold for the inner product, norm and distance function. Happily we find all the same general properties for the inner product and its induced norm and distance function.

Proposition 8.13.4.

If V is an inner product space with induced norm $\|\cdot\|$ and $x, y \in V$ then $|\langle x, y \rangle| \leq \|x\| \|y\|$.

Proof: since $\|x\| = \sqrt{\langle x, x \rangle}$ the proof we gave for the case of the dot-product equally well applies here. You'll notice in retrospect I only used those 4 properties which we take as the defining axioms for the inner product. \square

In fact, all the propositions from §8.1 apply equally well to an arbitrary finite-dimensional inner product space. The proof of the proposition below is similar to those I gave in §8.1

Proposition 8.13.5. *Properties for induced norm and distance function on an inner product space.*

If V is an inner product space with inner product $\langle \cdot, \cdot \rangle$ and norm $\|x\| = \sqrt{\langle x, x \rangle}$ and distance function $d(x, y) = \|y - x\|$ then for all $x, y, z \in V$ and $c \in \mathbb{R}$

- | | |
|---|---|
| (i.) $\ x\ \geq 0$ | (v.) $d(x, y) \geq 0$ |
| (ii.) $\ x\ = 0 \Leftrightarrow x = 0$ | (vi.) $d(x, y) = 0 \Leftrightarrow x = y$ |
| (iii.) $\ cx\ = c \ x\ $ | (vii.) $d(x, y) = d(y, x)$ |
| (iv.) $\ x + y\ \leq \ x\ + \ y\ $ | (viii.) $d(x, z) \leq d(x, y) + d(y, z)$ |

An norm is simply an operation which satisfies (i.) – (iv.). If we are given a vector space with a norm then that is called a normed linear space. If in addition all Cauchy sequences converge in the space it is said to be a complete normed linear space. A **Banach Space** is defined to be a complete normed linear space. A distance function is simply an operation which satisfies (v.) – (viii.). A set with a distance function is called a **metric space**. I'll let you ponder all these things in some other course, I mention them here merely for breadth. These topics are more interesting infinite-dimensional case.

What is truly interesting is that the orthogonal complement theorems and closest vector theory transfer over to the case of an inner product space.

Definition 8.13.6.

Let V be an inner product space with inner product $\langle \cdot, \cdot \rangle$. Let $x, y \in V$ then we say x is **orthogonal** to y iff $\langle x, y \rangle = 0$. A set S is said to be orthogonal iff every pair of vectors in S is orthogonal. If $W \leq V$ then the **orthogonal complement** of W is defined to be $W^\perp = \{v \in V \mid v \cdot w = 0 \ \forall w \in W\}$.

Proposition 8.13.7. *Orthogonality results for inner product space.*

If V is an inner product space with inner product $\langle \cdot, \cdot \rangle$ and norm $\|x\| = \sqrt{\langle x, x \rangle}$ then for all $x, y, z \in V$ and $W \leq V$,

- (i.) $\langle x, y \rangle = 0 \Rightarrow \|x + y\|^2 = \|x\|^2 + \|y\|^2$
- (ii.) if $S \subset V$ is orthogonal $\Rightarrow S$ is linearly independent
- (iii.) $S \subset V \Rightarrow S^\perp \leq V$
- (iv.) $W^\perp \cap W = \{0\}$
- (v.) $V = W \oplus W^\perp$

Definition 8.13.8.

Let V be an inner product space with inner product $\langle \cdot, \cdot \rangle$. A basis of $\langle \cdot, \cdot \rangle$ -orthogonal vectors is an **orthogonal basis**. Likewise, if every vector in an orthogonal basis has length one then we call it an **orthonormal basis**.

Every finite dimensional inner product space permits a choice of an orthonormal basis. Examine my proof in the case of the dot-product. You'll find I made all arguments on the basis of the axioms for an inner-product. The Gram-Schmidt process works equally well for inner product spaces, we just need to exchange dot-products for inner-products as appropriate.

Proposition 8.13.9. *Orthonormal coordinates and projection results.*

If V is an inner product space with inner product $\langle \cdot, \cdot \rangle$ and $\beta = \{v_1, v_2, \dots, v_k\}$ is a orthonormal basis for a subspace W then

- (i.) $w = \langle w, v_1 \rangle v_1 + \langle w, v_2 \rangle v_2 + \dots + \langle w, v_k \rangle v_k$ for each $w \in W$,
- (ii.) $Proj_W(x) \equiv \langle x, v_1 \rangle v_1 + \langle x, v_2 \rangle v_2 + \dots + \langle x, v_k \rangle v_k \in W$ for each $x \in V$,
- (iii.) $Orth_W(x) \equiv x - Proj_W(x) \in W^\perp$ for each $x \in V$,
- (iv.) $x = Proj_W(x) + Orth_W(x)$ and $\langle Proj_W(x), Orth_W(x) \rangle = 0$ for each $x \in V$,
- (v.) $\|x - Proj_W(x)\| < \|x - y\|$ for all $y \notin W$.

Notice that we can use the Gram-Schmidt idea to implement the least squares analysis in the context of an inner-product space. However, we cannot multiply abstract vectors by matrices so the short-cut normal equations may not make sense in this context. We have to implement the closest vector idea without the help of those normal equations. I'll demonstrate this idea in the Fourier analysis section.

8.13.1 examples of inner-products

The dot-product is just one of many inner products. We examine an assortment of other inner-products for various finite dimensional vector spaces.

Example 8.13.10. Let $V = \mathbb{R}^{2 \times 1}$ and define $\langle v, w \rangle = v_1 w_1 + 3v_2 w_2$ for all $v = [v_1, v_2]^T, w = [w_1, w_2]^T \in V$. Let $u, v, w \in V$ and $c \in \mathbb{R}$,

1. symmetric property,

$$\langle v, w \rangle = v_1 w_1 + 3v_2 w_2 = w_1 v_1 + 3w_2 v_2 = \langle w, v \rangle$$

2. additive property:

$$\begin{aligned} \langle u + v, w \rangle &= (u + v)_1 w_1 + 3(u + v)_2 w_2 \\ &= (u_1 + v_1) w_1 + 3(u_2 + v_2) w_2 \\ &= u_1 w_1 + v_1 w_1 + 3u_2 w_2 + 3v_2 w_2 \\ &= \langle u, w \rangle + \langle v, w \rangle \end{aligned}$$

3. homogeneous property:

$$\begin{aligned} \langle cv, w \rangle &= cv_1 w_1 + 3cv_2 w_2 \\ &= c(v_1 w_1 + 3v_2 w_2) \\ &= c \langle v, w \rangle \end{aligned}$$

4. positive definite property:

$$\langle v, v \rangle = v_1^2 + 3v_2^2 \geq 0 \text{ and } \langle v, v \rangle = 0 \Leftrightarrow v = 0.$$

Notice $e_1 = [1, 0]^T$ is an orthonormalized vector with respect to \langle, \rangle but $e_2 = [0, 1]^T$ not unit-length. Instead, $\langle e_2, e_2 \rangle = 3$ thus $\|e_2\| = \sqrt{3}$ so the unit-vector in the e_2 -direction is $u = \frac{1}{\sqrt{3}}[0, 1]^T$ and with respect to \langle, \rangle we have an orthonormal basis $\{e_1, u\}$.

Example 8.13.11. Let $V = \mathbb{R}^{m \times n}$ we define the Frobenious inner-product as follows:

$$\langle A, B \rangle = \sum_{i=1}^m \sum_{j=1}^n A_{ij} B_{ij}.$$

It is clear that $\langle A, A \rangle \geq 0$ since it is the sum of squares and it is also clear that $\langle A, A \rangle = 0$ iff $A = 0$. Symmetry follows from the calculation

$$\langle A, B \rangle = \sum_{i=1}^m \sum_{j=1}^n A_{ij} B_{ij} = \sum_{i=1}^m \sum_{j=1}^n B_{ij} A_{ij} = \langle B, A \rangle$$

where we can commute B_{ij} and A_{ij} for each pair i, j since the components are just real numbers. Linearity and homogeneity follow from:

$$\begin{aligned} \langle \lambda A + B, C \rangle &= \sum_{i=1}^m \sum_{j=1}^n (\lambda A + B)_{ij} C_{ij} = \sum_{i=1}^m \sum_{j=1}^n (\lambda A_{ij} + B_{ij}) C_{ij} \\ &= \lambda \sum_{i=1}^m \sum_{j=1}^n A_{ij} C_{ij} + \sum_{i=1}^m \sum_{j=1}^n B_{ij} C_{ij} = \lambda \langle A, C \rangle + \langle B, C \rangle \end{aligned}$$

Therefore, the Frobenius inner-product is in fact an inner product. The Frobenius norm of a matrix is induced as usual:

$$\|A\| = \sqrt{\langle A, A \rangle}$$

as a consequence of the theory in this chapter we already know a few interesting properties form the matrix-norm, in particular $\|\langle A, B \rangle\| \leq \|A\| \|B\|$. The particular case of square matrices allows further comments. If $A, B \in \mathbb{R}^{n \times n}$ then notice

$$\langle A, B \rangle = \sum_{i,j} A_{ij} B_{ij} = \sum_i \sum_j A_{ij} (B^T)_{ji} = \text{trace}(AB^T) \Rightarrow \|A\| = \text{trace}(AA^T)$$

We find an interesting identity for any square matrix $|\text{trace}(AB^T)| \leq \sqrt{\text{trace}(AA^T)\text{trace}(BB^T)}$.

Example 8.13.12. Let $C[a, b]$ denote the set of functions which are continuous on $[a, b]$. This is an infinite dimensional vector space. We can define an inner-product via the definite integral of the product of two functions: let $f, g \in C[a, b]$ define

$$\langle f, g \rangle = \int_a^b f(x)g(x)dx.$$

We can prove this is an inner-product. I'll just show additivity,

$$\begin{aligned} \langle f + g, h \rangle &= \int_a^b (f(x) + g(x))h(x)dx \\ &= \int_a^b f(x)h(x)dx + \int_a^b g(x)h(x)dx = \langle f, h \rangle + \langle g, h \rangle. \end{aligned}$$

I leave the proof of the other properties to the reader.

Example 8.13.13. Consider the inner-product $\langle f, g \rangle = \int_{-1}^1 f(x)g(x)dx$ for $f, g \in C[-1, 1]$. Let's calculate the length squared of the standard basis:

$$\begin{aligned} \langle 1, 1 \rangle &= \int_{-1}^1 1 \cdot 1 dx = 2, & \langle x, x \rangle &= \int_{-1}^1 x^2 dx = \frac{x^3}{3} \Big|_{-1}^1 = \frac{2}{3} \\ \langle x^2, x^2 \rangle &= \int_{-1}^1 x^4 dx = \frac{x^5}{5} \Big|_{-1}^1 = \frac{2}{5} \end{aligned}$$

Notice that the standard basis of P_2 are not all \langle, \rangle -orthogonal:

$$\langle 1, x \rangle = \int_{-1}^1 x dx = 0 \quad \langle 1, x^2 \rangle = \langle x, x \rangle = \int_{-1}^1 x^2 dx = \frac{2}{3} \quad \langle x, x^2 \rangle = \int_{-1}^1 x^3 dx = 0$$

We can use the Gram-Schmidt process on $\{1, x, x^2\}$ to find an orthonormal basis for P_2 on $[-1, 1]$. Let, $u_1(x) = 1$ and

$$\begin{aligned} u_2(x) &= x - \frac{\langle x, 1 \rangle}{\langle 1, 1 \rangle} = x \\ u_3(x) &= x^2 - \frac{\langle x^2, x \rangle}{\langle x, x \rangle} x - \frac{\langle x^2, 1 \rangle}{\langle 1, 1 \rangle} = x^2 - \frac{1}{3} \end{aligned}$$

We have an orthogonal set of functions $\{u_1, u_2, u_3\}$ we already calculated the length of u_1 and u_2 so we can immediately normalize those by dividing by their lengths; $v_1(x) = \frac{1}{\sqrt{2}}$ and $v_2(x) = \sqrt{\frac{3}{2}}x$. We need to calculate the length of u_3 so we can normalize it as well:

$$\langle u_3, u_3 \rangle = \int_{-1}^1 \left(x^2 - \frac{1}{3}\right)^2 dx = \int_{-1}^1 \left(x^4 - \frac{2}{3}x^2 + \frac{1}{9}\right) dx = \frac{2}{5} - \frac{4}{9} + \frac{2}{9} = \frac{8}{45}$$

Thus $v_3(x) = \sqrt{\frac{8}{45}}(x^2 - \frac{1}{3})$ has length one. Therefore, $\left\{\frac{1}{\sqrt{2}}, \sqrt{\frac{3}{2}}x, \sqrt{\frac{8}{45}}(x^2 - \frac{1}{3})\right\}$ is an orthonormal basis for P_2 restricted to $[-1, 1]$. Other intervals would not have the same basis. This construction depends both on our choice of inner-product and the interval considered. Incidentally, these are the first three **Legendre Polynomials**. These arise naturally as solutions to certain differential equations. The theory of **orthogonal polynomials** is full of such calculations. Orthogonal polynomials are quite useful as approximating functions. If we offered a second course in differential equations we could see the full function of such objects.

Example 8.13.14. Clearly $f(x) = e^x \notin P_2$. What is the least-squares approximation of f ? Use the projection onto P_2 : $\text{Proj}_{P_2}(f) = \langle f, v_1 \rangle v_1 + \langle f, v_2 \rangle v_2 + \langle f, v_3 \rangle v_3$. We calculate,

$$\langle f, v_1 \rangle = \int_{-1}^1 \frac{1}{\sqrt{2}} e^x dx = \frac{1}{\sqrt{2}}(e^1 - e^{-1}) \approx 1.661$$

$$\langle f, v_2 \rangle = \int_{-1}^1 \sqrt{\frac{3}{2}} x e^x dx = \sqrt{\frac{3}{2}} (x e^x - e^x) \Big|_{-1}^1 = \sqrt{\frac{3}{2}} [(-e^{-1} - e^{-1})] = \sqrt{6} e^{-1} \approx 0.901$$

$$\langle f, v_3 \rangle = \int_{-1}^1 \sqrt{\frac{8}{45}} \left(x^2 - \frac{1}{3}\right) e^x dx = \frac{2e}{3} - \frac{14e^{-1}}{3} \approx 0.0402$$

Thus,

$$\begin{aligned} \text{Proj}_{P_2}(f)(x) &= 1.661v_1(x) + 0.901v_2(x) + 0.0402v_3(x) \\ &= 1.03 + 1.103x + 0.017x^2 \end{aligned}$$

This is closest a quadratic can come to approximating the exponential function on the interval $[-1, 1]$. What's the giant theoretical leap we made in this example? We wouldn't face the same leap if we tried to approximate $f(x) = x^4$ with P_2 . What's the difference? Where does e^x live?

Example 8.13.15. Consider $C[-\pi, \pi]$ with inner product $\langle f, g \rangle = \int_{-\pi}^{\pi} f(x)g(x)dx$. The set of sine and cosine functions $\{1, \cos(x), \sin(x), \cos(2x), \sin(2x), \dots, \cos(kx), \sin(kx)\}$ is an orthogonal set of functions.

$$\langle \cos(mx), \cos(nx) \rangle = \int_{-\pi}^{\pi} \cos(mx) \cos(nx) dx = \pi \delta_{mn}$$

$$\langle \sin(mx), \sin(nx) \rangle = \int_{-\pi}^{\pi} \sin(mx) \sin(nx) dx = \pi \delta_{mn}$$

$$\langle \sin(mx), \cos(nx) \rangle = \int_{-\pi}^{\pi} \sin(mx) \cos(nx) dx = 0$$

Thus we find the following is a set of orthonormal functions

$$\beta_{trig} = \left\{ \frac{1}{\sqrt{2\pi}}, \frac{1}{\sqrt{\pi}} \cos(x), \frac{1}{\sqrt{\pi}} \sin(x), \frac{1}{\sqrt{\pi}} \cos(2x), \frac{1}{\sqrt{\pi}} \sin(2x), \dots, \frac{1}{\sqrt{\pi}} \cos(kx), \frac{1}{\sqrt{\pi}} \sin(kx) \right\}$$

8.13.2 Fourier analysis

The idea of Fourier analysis is based on the least-squares approximation and the last example of the preceding section. We wish to represent a function with a sum of sines and cosines, this is called a **Fourier sum**. Much like a power series, the more terms we use to approximate the function the closer the approximating sum of functions gets to the real function. In the limit the approximation can become exact, the Fourier sum goes to a Fourier series. I do not wish to confront the analytical issues pertaining to the convergence of Fourier series. As a practical matter, it's difficult to calculate infinitely many terms so in practice we just keep the first say 10 or 20 terms and it will come very close to the real function. The advantage of a Fourier sum over a polynomial is that sums of trigonometric functions have natural periodicities. If we approximate the function over the interval $[-\pi, \pi]$ we will also find our approximation repeats itself outside the interval. This is desirable if one wishes to model a wave-form of some sort. Enough talk. Time for an example. (there also an example in your text on pages 540-542 of Spence, Insel and Friedberg)

Example 8.13.16. Suppose $f(t) = \begin{cases} 1 & 0 < t < \pi \\ -1 & -\pi < t < 0 \end{cases}$ and $f(t + 2n\pi) = f(t)$ for all $n \in \mathbb{Z}$.

This is called a **square wave** for the obvious reason (draw its graph). Find the first few terms in a Fourier sum to represent the function. We'll want to use the projection: it's convenient to bring the normalizing constants out so we can focus on the integrals without too much clutter.¹⁵

$$\begin{aligned} Proj_W(f)(t) = & \frac{1}{2\pi} \langle f, 1 \rangle + \frac{1}{\pi} \langle f, \cos t \rangle \cos t + \frac{1}{\pi} \langle f, \sin t \rangle \sin t + \\ & + \frac{1}{\pi} \langle f, \cos 2t \rangle \cos 2t + \frac{1}{\pi} \langle f, \sin 2t \rangle \sin 2t + \dots \end{aligned}$$

Where $W = \text{span}(\beta_{trig})$. The square wave is constant on $(0, \pi]$ and $[-\pi, 0)$ and the value at zero is not defined (you can give it a particular value but that will not change the integrals that calculate the Fourier coefficients). Calculate,

$$\langle f, 1 \rangle = \int_{-\pi}^{\pi} f(t) dt = 0$$

$$\langle f, \cos t \rangle = \int_{-\pi}^{\pi} \cos(t) f(t) dt = 0$$

¹⁵In fact, various texts put these little normalization factors in different places so when you look up results on Fourier series beware conventional discrepancies

Notice that $f(t)$ and $\cos(t)f(t)$ are odd functions so we can conclude the integrals above are zero without further calculation. On the other hand, $\sin(-t)f(-t) = (-\sin t)(-f(t)) = \sin t f(t)$ thus $\sin(t)f(t)$ is an even function, thus:

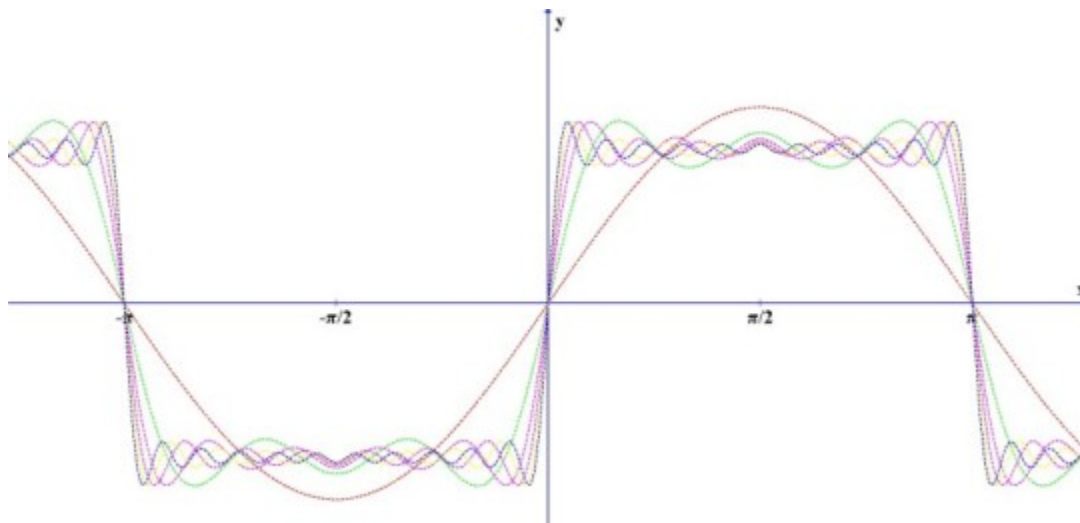
$$\langle f, \sin t \rangle = \int_{-\pi}^{\pi} \sin(t)f(t)dt = 2 \int_0^{\pi} \sin(t)f(t)dt = 2 \int_0^{\pi} \sin(t)dt = 4$$

Notice that $f(t)\cos(kt)$ is odd for all $k \in \mathbb{N}$ thus $\langle f, \cos(kt) \rangle = 0$. Whereas, $f(t)\sin(kt)$ is even for all $k \in \mathbb{N}$ thus

$$\begin{aligned} \langle f, \sin kt \rangle &= \int_{-\pi}^{\pi} \sin(kt)f(t)dt = 2 \int_0^{\pi} \sin(kt)f(t)dt \\ &= 2 \int_0^{\pi} \sin(kt)dt = \frac{2}{k} [1 - \cos(k\pi)] = \begin{cases} 0, & k \text{ even} \\ \frac{4}{k}, & k \text{ odd} \end{cases} \end{aligned}$$

Putting it all together we find (the \sim indicates the functions are nearly the same except for a finite subset of points),

$$f(t) \sim \frac{4}{\pi} \left(\sin t + \frac{1}{3} \sin 3t + \frac{1}{5} \sin 5t + \cdots \right) = \sum_{n=1}^{\infty} \frac{4}{(2n-1)\pi} \sin(2n-1)t$$



I have graphed the Fourier sums up the sum with 11 terms.

Remark 8.13.17.

The treatment of Fourier sums and series is by no means complete in these notes. There is much more to say and do. Our goal here is simply to connect Fourier analysis with the more general story of orthogonality. In the math 334 course we use Fourier series to construct solutions to partial differential equations. Those calculations are foundational to describe interesting physical examples such as the electric and magnetic fields in a waveguide, the vibrations of a drum, the flow of heat through some solid, even the vibrations of a string instrument.

Chapter 9

systems of differential equations

9.1 calculus of matrices

A more apt title would be "calculus of matrix-valued functions of a real variable".

Definition 9.1.1.

A matrix-valued function of a real variable is a function from $I \subseteq \mathbb{R}$ to $\mathbb{R}^{m \times n}$. Suppose $A : I \subseteq \mathbb{R} \rightarrow \mathbb{R}^{m \times n}$ is such that $A_{ij} : I \subseteq \mathbb{R} \rightarrow \mathbb{R}$ is differentiable for each i, j then we define

$$\frac{dA}{dt} = \left[\frac{dA_{ij}}{dt} \right]$$

which can also be denoted $(A')_{ij} = A'_{ij}$. We likewise define $\int A dt = [\int A_{ij} dt]$ for A with integrable components. Definite integrals and higher derivatives are also defined component-wise.

Example 9.1.2. Suppose $A(t) = \begin{bmatrix} 2t & 3t^2 \\ 4t^3 & 5t^4 \end{bmatrix}$. I'll calculate a few items just to illustrate the definition above. calculate; to differentiate a matrix we differentiate each component one at a time:

$$A'(t) = \begin{bmatrix} 2 & 6t \\ 12t^2 & 20t^3 \end{bmatrix} \quad A''(t) = \begin{bmatrix} 0 & 6 \\ 24t & 60t^2 \end{bmatrix} \quad A'(0) = \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix}$$

Integrate by integrating each component:

$$\int A(t) dt = \begin{bmatrix} t^2 + c_1 & t^3 + c_2 \\ t^4 + c_3 & t^5 + c_4 \end{bmatrix} \quad \int_0^2 A(t) dt = \begin{bmatrix} t^2|_0^2 & t^3|_0^2 \\ t^4|_0^2 & t^5|_0^2 \end{bmatrix} = \begin{bmatrix} 4 & 8 \\ 16 & 32 \end{bmatrix}$$

Proposition 9.1.3.

Suppose A, B are matrix-valued functions of a real variable, f is a function of a real variable, c is a constant, and C is a constant matrix then

1. $(AB)' = A'B + AB'$ (product rule for matrices)
2. $(AC)' = A'C$
3. $(CA)' = CA'$
4. $(fA)' = f'A + fA'$
5. $(cA)' = cA'$
6. $(A + B)' = A' + B'$

where each of the functions is evaluated at the same time t and I assume that the functions and matrices are differentiable at that value of t and of course the matrices A, B, C are such that the multiplications are well-defined.

Proof: Suppose $A(t) \in \mathbb{R}^{m \times n}$ and $B(t) \in \mathbb{R}^{n \times p}$ consider,

$$\begin{aligned}
 (AB)'_{ij} &= \frac{d}{dt}((AB)_{ij}) && \text{defn. derivative of matrix} \\
 &= \frac{d}{dt}(\sum_k A_{ik} B_{kj}) && \text{defn. of matrix multiplication} \\
 &= \sum_k \frac{d}{dt}(A_{ik} B_{kj}) && \text{linearity of derivative} \\
 &= \sum_k \left[\frac{dA_{ik}}{dt} B_{kj} + A_{ik} \frac{dB_{kj}}{dt} \right] && \text{ordinary product rules} \\
 &= \sum_k \frac{dA_{ik}}{dt} B_{kj} + \sum_k A_{ik} \frac{dB_{kj}}{dt} && \text{algebra} \\
 &= (A'B)_{ij} + (AB')_{ij} && \text{defn. of matrix multiplication} \\
 &= (A'B + AB')_{ij} && \text{defn. matrix addition}
 \end{aligned}$$

this proves (1.) as i, j were arbitrary in the calculation above. The proof of (2.) and (3.) follow quickly from (1.) since C constant means $C' = 0$. Proof of (4.) is similar to (1.):

$$\begin{aligned}
 (fA)'_{ij} &= \frac{d}{dt}((fA)_{ij}) && \text{defn. derivative of matrix} \\
 &= \frac{d}{dt}(fA_{ij}) && \text{defn. of scalar multiplication} \\
 &= \frac{df}{dt}A_{ij} + f\frac{dA_{ij}}{dt} && \text{ordinary product rule} \\
 &= \left(\frac{df}{dt}A + f\frac{dA}{dt} \right)_{ij} && \text{defn. matrix addition} \\
 &= \left(\frac{df}{dt}A + f\frac{dA}{dt} \right)_{ij} && \text{defn. scalar multiplication.}
 \end{aligned}$$

The proof of (5.) follows from taking $f(t) = c$ which has $f' = 0$. I leave the proof of (6.) as an exercise for the reader. \square .

To summarize: the calculus of matrices is the same as the calculus of functions with the small qualifier that we must respect the rules of matrix algebra. The noncommutativity of matrix multiplication is the main distinguishing feature.

Since we're discussing this type of differentiation perhaps it would be worthwhile for me to insert a comment about complex functions here. Differentiation of functions from \mathbb{R} to \mathbb{C} is defined by splitting a given function into its real and imaginary parts then we just differentiate with respect to the real variable one component at a time. For example:

$$\begin{aligned}
 \frac{d}{dt}(e^{2t} \cos(t) + ie^{2t} \sin(t)) &= \frac{d}{dt}(e^{2t} \cos(t)) + i \frac{d}{dt}(e^{2t} \sin(t)) \\
 &= (2e^{2t} \cos(t) - e^{2t} \sin(t)) + i(2e^{2t} \sin(t) + e^{2t} \cos(t)) \quad (9.1) \\
 &= e^{2t}(2 + i)(\cos(t) + i \sin(t)) \\
 &= (2 + i)e^{(2+i)t}
 \end{aligned}$$

where I have made use of the identity¹ $e^{x+iy} = e^x(\cos(y) + i \sin(y))$. We just saw that

$$\frac{d}{dt}e^{\lambda t} = \lambda e^{\lambda t}$$

which seems obvious enough until you appreciate that we just proved it for $\lambda = 2 + i$. We make use of this calculation in the next section in the case we have complex e-values.

9.2 introduction to systems of linear differential equations

A differential equation (DEqn) is simply an equation that is stated in terms of derivatives. The highest order derivative that appears in the DEqn is called the *order* of the DEqn. In calculus we learned to integrate. Recall that $\int f(x)dx = y$ iff $\frac{dy}{dx} = f(x)$. Everytime you do an integral you are solving a first order DEqn. In fact, it's an *ordinary* DEqn (ODE) since there is only one independent variable (it was x). A system of ODEs is a set of differential equations with a common independent variable. It turns out that any linear differential equation can be written as a system of ODEs in *normal form*. I'll define *normal form* then illustrate with a few examples.

Definition 9.2.1.

¹or definition, depending on how you choose to set-up the complex exponential, I take this as the definition in calculus II

Let t be a real variable and suppose x_1, x_2, \dots, x_n are functions of t . If A_{ij}, f_i are functions of t for all $1 \leq i \leq m$ and $1 \leq j \leq n$ then the following set of differential equations is defined to be a system of linear differential equations in **normal form**:

$$\begin{aligned}\frac{dx_1}{dt} &= A_{11}x_1 + A_{12}x_2 + \cdots A_{1n}x_n + f_1 \\ \frac{dx_2}{dt} &= A_{21}x_1 + A_{22}x_2 + \cdots A_{2n}x_n + f_2 \\ &\vdots = \vdots \quad \vdots \quad \cdots \quad \vdots \\ \frac{dx_m}{dt} &= A_{m1}x_1 + A_{m2}x_2 + \cdots A_{mn}x_n + f_m\end{aligned}$$

In matrix notation, $\frac{dx}{dt} = Ax + f$. The system is called homogeneous if $f = 0$ whereas the system is called nonhomogeneous if $f \neq 0$. The system is called **constant coefficient** if $\frac{d}{dt}(A_{ij}) = 0$ for all i, j . If $m = n$ and a set of initial conditions $x_1(t_0) = y_1, x_2(t_0) = y_2, \dots, x_n(t_0) = y_n$ are given then this is called an **initial value problem (IVP)**.

Example 9.2.2. If x is the number of tigers and y is the number of rabbits then

$$\frac{dx}{dt} = x + y \qquad \frac{dy}{dt} = -100x + 20y$$

is a model for the population growth of tigers and bunnies in some closed environment. My logic for my made-up example is as follows: the coefficient 1 is the growth rate for tigers which don't breed to quickly. Whereas the growth rate for bunnies is 20 since bunnies reproduce like, well bunnies. Then the y in the $\frac{dx}{dt}$ equation goes to account for the fact that more bunnies means more tiger food and hence the tiger reproduction should speed up (this is probably a bogus term, but this is my made up example so deal). Then the $-100x$ term accounts for the fact that more tigers means more tigers eating bunnies so naturally this should be negative. In matrix form

$$\begin{bmatrix} \frac{dx}{dt} \\ \frac{dy}{dt} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ -100 & 20 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

How do we solve such a system? This is the question we seek to answer.

The preceding example is a *predator-prey* model. There are many other terms that can be added to make the model more realistic. Ultimately all population growth models are only useful if they can account for all significant effects. History has shown population growth models are of only limited use for humans.

Example 9.2.3. Reduction of Order in calculus II you may have studied how to solve $y'' + by' + cy = 0$ for any choice of constants b, c . This is a second order ODE. We can reduce it to a system of first order ODEs by introducing new variables: $x_1 = y$ and $x_2 = y'$ then we have

$$x'_1 = y' = x_2$$

and,

$$x'_2 = y'' = -by' - cy = -bx_2 - cx_1$$

As a matrix DEqn,

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}' = \begin{bmatrix} 0 & 1 \\ -c & -b \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

Similarly if $y'''' + 2y''' + 3y'' + 4y' + 5y = 0$ we can introduce variables to reduce the order: $x_1 = y, x_2 = y', x_3 = y'', x_4 = y'''$ then you can show:

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}' = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -5 & -4 & -3 & -2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

is equivalent to $y'''' + 2y''' + 3y'' + 4y' + 5y = 0$. We call the matrix above the **companion matrix** of the n -th order constant coefficient ODE. There is a beautiful interplay between solutions to n -th order ODEs and the linear algebra of the companion matrix.

Example 9.2.4. Suppose $y'' + 4y' + 5y = 0$ and $x'' + x = 0$. This is a system of linear second order ODEs. It can be recast as a system of 4 first order ODEs by introducing new variables: $x_1 = y, x_2 = y', x_3 = x, x_4 = x'$. In matrix form the given system in normal form is:

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}' = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -5 & -4 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

The companion matrix above will be found to have eigenvalues $\lambda = -2 \pm i$ and $\lambda = \pm i$. I know this without further calculation purely on the basis of what I know from DEqns and the interplay I alluded to in the last example.

Example 9.2.5. If $y'''' + 2y'' + y = 0$ we can introduce variables to reduce the order: $x_1 = y, x_2 = y', x_3 = y'', x_4 = y'''$ then you can show:

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}' = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -1 & 0 & -2 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$$

is equivalent to $y'''' + 2y'' + y = 0$. If we solve the matrix system then we solve the equation in y and vice-versa. I happen to know the solution to the y equation is $y = c_1 \cos t + c_2 \sin t + c_3 t \cos t + c_4 t \sin t$. From this I can deduce that the companion matrix has a repeated e -value of $\lambda = \pm i$ and just one complex e -vector and its conjugate. This matrix would answer the bonus point question I posed a few sections back. I invite the reader to verify my claims.

Remark 9.2.6.

For those of you who will or have taken math 334 my guesswork above is predicated on two observations:

1. the "auxillary" or "characteristic" equation in the study of the constant coefficient ODEs is identical to the characteristic equation of the companion matrix.
2. ultimately eigenvectors will give us exponentials and sines and cosines in the solution to the matrix ODE whereas solutions which have multiplications by t stem from generalized e-vectors. Conversely, if the DEqn has a t or t^2 multiplying cosine, sine or exponential functions then the companion matrix must in turn have generalized e-vectors to account for the t or t^2 etc...

I will not explain (1.) in this course, however we will hopefully make sense of (2.) by the end of this section.

9.3 the matrix exponential

Perhaps the most important first order ODE is $\frac{dy}{dt} = ay$. This DEqn says that the rate of change in y is simply proportional to the amount of y at time t . Geometrically, this DEqn states the solutions value is proportional to its slope at every point in its domain. The solution² is the exponential function $y(t) = e^{at}$.

We face a new differential equation; $\frac{dx}{dt} = Ax$ where x is a vector-valued function of t and $A \in \mathbb{R}^{n \times n}$. Given our success with the exponential function for the scalar case is it not natural to suppose that $x = e^{tA}$ is the solution to the matrix DEqn? The answer is yes. However, we need to define a few items before we can understand the true structure of the claim.

Definition 9.3.1.

Let $A \in \mathbb{R}^{n \times n}$ define $e^A \in \mathbb{R}^{n \times n}$ by the following formula

$$e^A = \sum_{n=0}^{\infty} \frac{1}{n!} A^n = I + A + \frac{1}{2}A^2 + \frac{1}{3!}A^3 + \cdots.$$

We also denote $e^A = \exp(A)$ when convenient.

This definition is the natural extension of the Taylor series formula for the exponential function we derived in calculus II. Of course, you should be skeptical of this definition. How do I even know the series converges for an arbitrary matrix A ? And, what do I even mean by "converge" for a series of matrices? (skip the next subsection if you don't care)

²ok, technically separation of variables yields the general solution $y = ce^{at}$ but I'm trying to focus on the exponential function for the moment.

9.3.1 analysis for matrices

Remark 9.3.2.

The purpose of this section is to alert the reader to the gap in the development here. We will use the matrix exponential despite our inability to fully grasp the underlying analysis. Much in the same way we calculate series in calculus without proving every last theorem. I will attempt to at least sketch the analytical underpinnings of the matrix exponential. The reader will be happy to learn this is not part of the required material.

We use the Frobenius norm for $A \in \mathbb{R}^{n \times n}$, $\|A\| = \sqrt{\sum_{i,j} (A_{ij})^2}$. We already proved this was a norm in a previous chapter. A sequence of square matrices is a function from \mathbb{N} to $\mathbb{R}^{n \times n}$. We say the sequence $\{A_n\}_{n=1}^{\infty}$ converges to $L \in \mathbb{R}^{n \times n}$ iff for each $\epsilon > 0$ there exists $M \in \mathbb{N}$ such that $\|A_n - L\| < \epsilon$ for all $n > M$. This is the same definition we used in calculus, just now the norm is the Frobenius norm and the functions are replaced by matrices. The definition of a series is also analogous to the definition you learned in calculus II.

Definition 9.3.3.

Let $A_k \in \mathbb{R}^{m \times m}$ for all k , the sequence of partial sums of $\sum_{k=0}^{\infty} A_k$ is given by $S_n = \sum_{k=1}^n A_k$. We say the series $\sum_{k=0}^{\infty} A_k$ converges to $L \in \mathbb{R}^{m \times m}$ iff the sequence of partial sums converges to L . In other words,

$$\sum_{k=1}^{\infty} A_k = \lim_{n \rightarrow \infty} \sum_{k=1}^n A_k.$$

Many of the same theorems hold for matrices:

Proposition 9.3.4.

Let $t \rightarrow S_A(t) = \sum A_k(t)$ and $t \rightarrow S_B(t) = \sum_k B_k(t)$ be matrix valued functions of a real variable t where the series are uniformly convergent and $c \in \mathbb{R}$ then

1. $\sum_k cA_k = c \sum_k A_k$
2. $\sum_k (A_k + B_k) = \sum_k A_k + \sum_k B_k$
3. $\frac{d}{dt} [\sum_k A_k] = \sum_k \frac{d}{dt} [A_k]$
4. $\int [\sum_k A_k] dt = C + \sum_k \int A_k dt$ where C is a constant matrix.

The summations can go to infinity and the starting index can be any integer.

Uniform convergence means the series converge without regard to the value of t . Let me just refer you to the analysis course, we should discuss uniform convergence in that course, the concept equally well applies here. It is the crucial fact which one needs to interchange the limits which are implicit within \sum_k and $\frac{d}{dt}$. There are counterexamples in the case the series is not uniformly convergent. Fortunately,

Proposition 9.3.5.

Let A be a square matrix then $\exp(A) = \sum_{k=0}^{\infty} \frac{1}{k!} A^k$ is a uniformly convergent series of matrices.

Basically, the argument is as follows: The set of square matrices with the Frobenius norm is isometric to \mathbb{R}^{n^2} which is a complete space. A complete space is one in which every Cauchy sequence converges. We can show that the sequence of partial sums for $\exp(A)$ is a Cauchy sequence in $\mathbb{R}^{n \times n}$ hence it converges. Obviously I'm leaving some details out here. You can look at the excellent *Calculus* text by Apostol to see more gory details. Also, if you don't like my approach to the matrix exponential then he has several other ways to look it.

(Past this point I expect you to start following along again.)

9.3.2 formulas for the matrix exponential

Now for the fun part.

Proposition 9.3.6.

Let A be a square matrix then $\frac{d}{dt} [\exp(tA)] = A \exp(tA)$

Proof: I'll give the proof in two notations. First,

$$\begin{aligned}
 \frac{d}{dt} [\exp(tA)] &= \frac{d}{dt} \left[\sum_{k=0}^{\infty} \frac{1}{k!} t^k A^k \right] && \text{defn. of matrix exponential} \\
 &= \sum_{k=0}^{\infty} \frac{d}{dt} \left[\frac{1}{k!} t^k A^k \right] && \text{since matrix exp. uniformly conv.} \\
 &= \sum_{k=0}^{\infty} \frac{k}{k!} t^{k-1} A^k && A^k \text{ constant and } \frac{d}{dt}(t^k) = kt^{k-1} \\
 &= A \sum_{k=1}^{\infty} \frac{1}{(k-1)!} t^{k-1} A^{k-1} && \text{since } k! = k(k-1)! \text{ and } A^k = AA^{k-1}. \\
 &= A \exp(tA) && \text{defn. of matrix exponential.}
 \end{aligned}$$

I suspect the following argument is easier to follow:

$$\begin{aligned}
 \frac{d}{dt} (\exp(tA)) &= \frac{d}{dt} (I + tA + \frac{1}{2}t^2A^2 + \frac{1}{3!}t^3A^3 + \cdots) \\
 &= \frac{d}{dt}(I) + \frac{d}{dt}(tA) + \frac{1}{2} \frac{d}{dt}(t^2A^2) + \frac{1}{3 \cdot 2} \frac{d}{dt}(t^3A^3) + \cdots \\
 &= A + tA^2 + \frac{1}{2}t^2A^3 + \cdots \\
 &= A(I + tA + \frac{1}{2}t^2A^2 + \cdots) \\
 &= A \exp(tA).
 \end{aligned}$$

□

Notice that we have all we need to see that $\exp(tA)$ is a matrix of solutions to the differential equation $x' = Ax$. The following prop. follows from the preceding prop. and Prop. 3.3.12.

Proposition 9.3.7.

If $X = \exp(tA)$ then $X' = A\exp(tA) = AX$. This means that each column in X is a solution to $x' = Ax$.

Let us illustrate this proposition with a particularly simple example.

Example 9.3.8. Suppose $x' = x, y' = 2y, z' = 3z$ then in matrix form we have:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix}' = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

The coefficient matrix is diagonal which makes the k -th power particularly easy to calculate,

$$\begin{aligned} A^k &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix}^k = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2^k & 0 \\ 0 & 0 & 3^k \end{bmatrix} \\ \Rightarrow \exp(tA) &= \sum_{k=0}^{\infty} \frac{t^k}{k!} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2^k & 0 \\ 0 & 0 & 3^k \end{bmatrix} = \begin{bmatrix} \sum_{k=0}^{\infty} \frac{t^k}{k!} 1^k & 0 & 0 \\ 0 & \sum_{k=0}^{\infty} \frac{t^k}{k!} 2^k & 0 \\ 0 & 0 & \sum_{k=0}^{\infty} \frac{t^k}{k!} 3^k \end{bmatrix} \\ \Rightarrow \exp(tA) &= \begin{bmatrix} e^t & 0 & 0 \\ 0 & e^{2t} & 0 \\ 0 & 0 & e^{3t} \end{bmatrix} \end{aligned}$$

Thus we find three solutions to $x' = Ax$,

$$x_1(t) = \begin{bmatrix} e^t \\ 0 \\ 0 \end{bmatrix} \quad x_2(t) = \begin{bmatrix} 0 \\ e^{2t} \\ 0 \end{bmatrix} \quad x_3(t) = \begin{bmatrix} 0 \\ 0 \\ e^{3t} \end{bmatrix}$$

In turn these vector solutions amount to the solutions $x = e^t, y = 0, z = 0$ or $x = 0, y = e^{2t}, z = 0$ or $x = 0, y = 0, z = e^{3t}$. It is easy to check these solutions.

Usually we cannot calculate the matrix exponential explicitly by such a straightforward calculation. We need e-vectors and sometimes generalized e-vectors to reliably calculate the solutions of interest.

Proposition 9.3.9.

If A, B are square matrices such that $AB = BA$ then $e^{A+B} = e^A e^B$

Proof: I'll show how this works for terms up to quadratic order,

$$e^A e^B = (1 + A + \frac{1}{2}A^2 + \cdots)(1 + B + \frac{1}{2}B^2 + \cdots) = 1 + (A + B) + \frac{1}{2}A^2 + AB + \frac{1}{2}B^2 + \cdots.$$

However, since $AB = BA$ and

$$(A + B)^2 = (A + B)(A + B) = A^2 + AB + BA + B^2 = A^2 + 2AB + B^2.$$

Thus,

$$e^A e^B = 1 + (A + B) + \frac{1}{2}(A + B)^2 + \cdots = e^{A+B} \quad \square$$

You might wonder what happens if $AB \neq BA$. In this case we can account for the departure from commutativity by the **commutator** of A and B .

Definition 9.3.10.

Let $A, B \in \mathbb{R}^{n \times n}$ then the **commutator** of A and B is $[A, B] = AB - BA$.

Proposition 9.3.11.

Let $A, B, C \in \mathbb{R}^{n \times n}$ then

1. $[A, B] = -[B, A]$
2. $[A + B, C] = [A, C] + [B, C]$
3. $[AB, C] = A[B, C] + [A, C]B$
4. $[A, BC] = B[A, C] + [A, B]C$
5. $[[A, B], C] + [[B, C], A] + [[C, A], B] = 0$

The proofs of the properties above are not difficult. In contrast, the following formula known as the Baker-Campbell-Hausdorff (BCH) relation takes considerably more calculation:

$$e^A e^B = e^{A+B+\frac{1}{2}[A,B]+\frac{1}{12}[[A,B],B]+\frac{1}{12}[[B,A],A]+\cdots} \quad \text{BCH-formula}$$

The higher order terms can also be written in terms of nested commutators. What this means is that if we know the values of the commutators of two matrices then we can calculate the product of their exponentials with a little patience. This connection between multiplication of exponentials and commutators of matrices is at the heart of Lie theory. Actually, mathematicians have greatly abstracted the idea of Lie algebras and Lie groups way past matrices but the concrete example of matrix Lie groups and algebras is perhaps the most satisfying. If you'd like to know more just ask. It would make an excellent topic for an independent study that extended this course.

Remark 9.3.12.

In fact the *BCH* holds in the abstract as well. For example, it holds for the Lie algebra of derivations on smooth functions. A *derivation* is a linear differential operator which satisfies the product rule. The derivative operator is a derivation since $D[fg] = D[f]g + fD[g]$. The commutator of derivations is defined by $[X, Y][f] = X(Y(f)) - Y(X(f))$. It can be shown that $[D, D] = 0$ thus the BCH formula yields

$$e^{aD}e^{bD} = e^{(a+b)D}.$$

If the coefficient of D is thought of as position then multiplication by e^{bD} generates a translation in the position. By the way, we can state Taylor's Theorem rather compactly in this operator notation: $f(x+h) = \exp(hD)f(x) = f(x) + hf'(x) + \frac{h^2}{2}f''(x) + \frac{h^3}{3!}f'''(x) + \dots$.

Proposition 9.3.13.

Let $A, P \in \mathbb{R}^{n \times n}$ and assume P is invertible then

$$\exp(P^{-1}AP) = P^{-1}\exp(A)P$$

Proof: this identity follows from the following observation:

$$(P^{-1}AP)^k = P^{-1}APP^{-1}APP^{-1}AP \dots P^{-1}AP = P^{-1}A^kP.$$

Thus $\exp(P^{-1}AP) = \sum_{k=0}^{\infty} \frac{1}{k!} (P^{-1}AP)^k = P^{-1}(\sum_{k=0}^{\infty} \frac{1}{k!} A^k)P = P^{-1}\exp(A)P$. \square

Proposition 9.3.14.

Let A be a square matrix, $\det(\exp(A)) = \exp(\text{trace}(A))$.

Proof: If the matrix A is diagonalizable then the proof is simple. Diagonalizability means there exists invertible $P = [v_1|v_2|\dots|v_n]$ such that $P^{-1}AP = D = [\lambda_1 v_1|\lambda_2 v_2|\dots|\lambda_n v_n]$ where v_i is an e-vector with e-value λ_i for all i . Use the preceding proposition to calculate

$$\det(\exp(D)) = \det(\exp(P^{-1}AP)) = \det(P^{-1}\exp(A)P) = \det(P^{-1}P)\det(\exp(A)) = \det(\exp(A))$$

On the other hand, the trace is cyclic $\text{trace}(ABC) = \text{trace}(BCA)$

$$\text{trace}(D) = \text{trace}(P^{-1}AP) = \text{trace}(PP^{-1}A) = \text{trace}(A)$$

But, we also know D is diagonal with eigenvalues on the diagonal hence $\exp(D)$ is diagonal with e^{λ_i} on the corresponding diagonals

$$\det(\exp(D)) = e^{\lambda_1}e^{\lambda_2}\dots e^{\lambda_n} \quad \text{and} \quad \text{trace}(D) = \lambda_1 + \lambda_2 + \dots + \lambda_n$$

Finally, use the laws of exponents to complete the proof,

$$e^{\text{trace}(A)} = e^{\text{trace}(D)} = e^{\lambda_1 + \lambda_2 + \dots + \lambda_n} = e^{\lambda_1}e^{\lambda_2}\dots e^{\lambda_n} = \det(\exp(D)) = \det(\exp(A)).$$

I've seen this proof in texts presented as if it were the general proof. But, not all matrices are diagonalizable so this is a curious proof. I stated the proposition for an arbitrary matrix and I meant it. The proof, the real proof, is less obvious. Let me sketch it for you:

better proof: The preceding proof shows it may be hopeful to suppose that $\det(\exp(tA)) = \exp(t \operatorname{trace}(A))$ for $t \in \mathbb{R}$. Notice that $y = e^{kt}$ satisfies the differential equation $\frac{dy}{dt} = ky$. Conversely, if $\frac{dy}{dt} = ky$ for some constant k then the general solution is given by $y = c_0 e^{kt}$ for some $c_0 \in \mathbb{R}$. Let $f(t) = \det(\exp(tA))$. If we can show that $f'(t) = \operatorname{trace}(A)f(t)$ then we can conclude $f(t) = c_0 e^{t \operatorname{trace}(A)}$. Consider:

$$\begin{aligned}
 f'(t) &= \frac{d}{dh} \left(f(t+h) \right) \Big|_{h=0} \\
 &= \frac{d}{dh} \left(\det(\exp[(t+h)A]) \right) \Big|_{h=0} \\
 &= \frac{d}{dh} \left(\det(\exp[tA + hA]) \right) \Big|_{h=0} \\
 &= \frac{d}{dh} \left(\det(\exp[tA] \exp[hA]) \right) \Big|_{h=0} \\
 &= \det(\exp[tA]) \frac{d}{dh} \left(\det(\exp[hA]) \right) \Big|_{h=0} \\
 &= f(t) \frac{d}{dh} \left(\det(I + hA + \frac{1}{2}h^2 A^2 + \frac{1}{3!}h^3 A^3 + \cdots) \right) \Big|_{h=0} \\
 &= f(t) \frac{d}{dh} \left(\det(I + hA) \right) \Big|_{h=0}
 \end{aligned}$$

Let us discuss the $\frac{d}{dh}(\det(I + hA))$ term separately for a moment:³

$$\begin{aligned}
 \frac{d}{dh}(\det(I + hA)) &= \frac{d}{dh} \left[\sum_{i_1, \dots, i_n} \epsilon_{i_1 i_2 \dots i_n} (I + hA)_{i_1 1} (I + hA)_{i_2 2} \cdots (I + hA)_{i_n n} \right]_{h=0} \\
 &= \sum_{i_1, \dots, i_n} \epsilon_{i_1 i_2 \dots i_n} \frac{d}{dh} [(I + hA)_{i_1 1} (I + hA)_{i_2 2} \cdots (I + hA)_{i_n n}]_{h=0} \\
 &= \sum_{i_1, \dots, i_n} \epsilon_{i_1 i_2 \dots i_n} (A_{1 i_1} I_{i_2} \cdots I_{i_n} + I_{1 i_1} A_{2 i_2} \cdots I_{i_n} + \cdots + I_{1 i_1} I_{2 i_2} \cdots A_{n i_n}) \\
 &= \sum_{i_1} \epsilon_{i_1 2 \dots n} A_{1 i_1} + \sum_{i_2} \epsilon_{1 i_2 \dots n} A_{2 i_2} + \cdots + \sum_{i_n} \epsilon_{1 2 \dots i_n} A_{n i_n} \\
 &= A_{11} + A_{22} + \cdots + A_{nn} \\
 &= \operatorname{trace}(A)
 \end{aligned}$$

³I use the definition of the identity matrix $I_{ij} = \delta_{ij}$ in eliminating all but the last summation in the fourth line. Then the levi-civita symbols serve the same purpose in going to the fifth line as $\epsilon_{i_1 2 \dots n} = \delta_{1 i_1}, \epsilon_{1 i_2 \dots n} = \delta_{2 i_2}$ etc...

Therefore, $f'(t) = \text{trace}(A)f(t)$ consequently, $f(t) = c_o e^{t \text{trace}(A)} = \det(\exp(tA))$. However, we can resolve c_o by calculating $f(0) = \det(\exp(0)) = \det(I) = 1 = c_o$ hence

$$e^{t \text{trace}(A)} = \det(\exp(tA))$$

Take $t = 1$ to obtain the desired result. \square

Remark 9.3.15.

The formula $\det(\exp(A)) = \exp(\text{trace}(A))$ is very important to the theory of matrix Lie groups and Lie algebras. Generically, if G is the Lie group and \mathfrak{g} is the Lie algebra then they are connected via the matrix exponential: $\exp : \mathfrak{g} \rightarrow G_o$ where I mean G_o to denote the connected component of the identity. For example, the set of all nonsingular matrices $GL(n)$ forms a Lie group which is disconnected. Half of $GL(n)$ has positive determinant whereas the other half has negative determinant. The set of all $n \times n$ matrices is denoted $gl(n)$ and it can be shown that $\exp(gl(n))$ maps onto the part of $GL(n)$ which has positive determinant. One can even define a matrix logarithm map which serves as a local inverse for the matrix exponential near the identity. Generally the matrix exponential is not injective thus some technical considerations must be discussed before we could put the matrix log on a solid footing. This would take us outside the scope of this course. However, this would be a nice topic to do a follow-up independent study. The theory of matrix Lie groups and their representations is ubiquitous in modern quantum mechanical physics.

Finally, we come to the formula that is most important to our study of systems of DEqns. Let's call this the magic formula.

Proposition 9.3.16.

Let $\lambda \in \mathbb{C}$ and suppose $A \in \mathbb{R}^{n \times n}$ then

$$\exp(tA) = e^{\lambda t} \left(I + t(A - \lambda I) + \frac{t^2}{2}(A - \lambda I)^2 + \frac{t^3}{3!}(A - \lambda I)^3 + \cdots \right).$$

Proof: Notice that $tA = t(A - \lambda I) + t\lambda I$ and $t\lambda I$ commutes with all matrices thus,

$$\begin{aligned} \exp(tA) &= \exp(t(A - \lambda I) + t\lambda I) \\ &= \exp(t(A - \lambda I))\exp(t\lambda I) \\ &= e^{\lambda t} \exp(t(A - \lambda I)) \\ &= e^{\lambda t} \left(I + t(A - \lambda I) + \frac{t^2}{2}(A - \lambda I)^2 + \frac{t^3}{3!}(A - \lambda I)^3 + \cdots \right) \end{aligned}$$

In the third line I used the identity proved below,

$$\exp(t\lambda I) = I + t\lambda I + \frac{1}{2}(t\lambda)^2 I^2 + \cdots = I \left(1 + t\lambda + \frac{(t\lambda)^2}{2} + \cdots \right) = Ie^{t\lambda}. \quad \square$$

While the proofs leading up to the magic formula only dealt with real matrices it is not hard to see the proofs are easily modified to allow for complex matrices.

9.4 solutions for systems of DEqns with real eigenvalues

Let us return to the problem of solving $\vec{x}' = A\vec{x}$ for a constant square matrix A where $\vec{x} = [x_1, x_2, \dots, x_n]$ is a vector of functions of t . I'm adding the vector notation to help distinguish the scalar function x_1 from the vector function \vec{x}_1 in this section. Let me state one theorem from the theory of differential equations. The existence of solutions theorem which is the heart of of this theorem is fairly involved to prove, you'll find it in one of the later chapters of the differential equations text by Nagel Saff and Snider.

Theorem 9.4.1.

If $\vec{x}' = A\vec{x}$ and A is a constant matrix then any solution to the system has the form

$$\vec{x}(t) = c_1 \vec{x}_1(t) + c_2 \vec{x}_2(t) + \cdots + c_n \vec{x}_n(t)$$

where $\{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_n\}$ is a linearly independent set of solutions defined on \mathbb{R} (this is called the **fundamental solution set**). Moreover, these fundamental solutions can be concatenated into a single invertible solution matrix called the **fundamental matrix** $X = [\vec{x}_1 | \vec{x}_2 | \cdots | \vec{x}_n]$ and the general solution can be expressed as $\vec{x}(t) = X(t)\vec{c}$ where \vec{c} is an arbitrary vector of real constants. If an initial condition $\vec{x}(t_o) = \vec{x}_o$ is given then the solution to the IVP is $\vec{x}(t) = X^{-1}(t_o)X(t_o)\vec{x}_o$.

We proved in the previous section that the matrix exponential $\exp(tA)$ is a solution matrix and the inverse is easy enough to guess: $\exp(tA)^{-1} = \exp(-tA)$. This proves the columns of $\exp(tA)$ are solutions to $\vec{x}' = A\vec{x}$ which are linearly independent and as such form a fundamental solution set.

Problem: we cannot directly calculate $\exp(tA)$ for most matrices A . We have a solution we can't calculate. What good is that?

When can we explicitly calculate $\exp(tA)$ without much thought? Two cases come to mind: (1.) if A is diagonal then it's easy, saw this in Example 9.3.8, (2.) if A is a **nilpotent** matrix then there is some finite power of the matrix which is zero; $A^k = 0$. In the nilpotent case the infinite series defining the matrix exponential truncates at order k :

$$\exp(tA) = I + tA + \frac{t^2}{2}A^2 + \cdots + \frac{t^{k-1}}{(k-1)!}A^{k-1}$$

Example 9.4.2. Let $A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$ we calculate $A^2 = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$ thus

$$\exp(tA) = I + tA = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + t \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & t \\ 0 & 1 \end{bmatrix}$$

Incidentally, the solution to $\vec{x}' = A\vec{x}$ is generally $\vec{x}(t) = c_1 \begin{bmatrix} 1 \\ 0 \end{bmatrix} + c_2 \begin{bmatrix} t \\ 1 \end{bmatrix}$. In other words, $x_1(t) = c_1 + c_2 t$ whereas $x_2(t) = c_2$. These solutions are easily seen to solve the system $x_1' = x_2$ and $x_2' = 0$.

Unfortunately, the calculation we just did in the last example almost never works. For example, try to calculate an arbitrary power of $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$, let me know how it works out. We would like for all examples to truncate. The **magic formula** gives us a way around this dilemma:

Proposition 9.4.3.

Let $A \in \mathbb{R}^{n \times n}$. Suppose v is an e-vector with e-value λ then $\exp(tA)v = e^{\lambda t}v$.

Proof: we are given that $(A - \lambda I)v = 0$ and it follows that $(A - \lambda I)^k v = 0$ for all $k \geq 1$. Use the magic formula,

$$\exp(tA)v = e^{\lambda t}(I + t(A - \lambda I) + \cdots)v = e^{\lambda t}(Iv + t(A - \lambda I)v + \cdots) = e^{\lambda t}v$$

noting all the higher order terms vanish since $(A - \lambda I)^k v = 0$. \square

We can't hope for the matrix exponential itself to truncate, but when we multiply $\exp(tA)$ on an e-vector something special happens. Since $e^{\lambda t} \neq 0$ the set of vector functions $\{e^{\lambda_1 t}v_1, e^{\lambda_2 t}v_2, \dots, e^{\lambda_k t}v_k\}$ will be linearly independent if the e-vectors v_i are linearly independent. If

the matrix A is diagonalizable then we'll be able to find enough e-vectors to construct a fundamental solution set using e-vectors alone. However, if A is not diagonalizable, and has only real e-values, then we can still find a Jordan basis $\{v_1, v_2, \dots, v_n\}$ which consists of generalized e-vectors and it follows that $\{e^{tA}v_1, e^{tA}v_2, \dots, e^{tA}v_n\}$ forms a fundamental solution set. Moreover, this is not just of theoretical use. We can actually calculate this solution set.

Proposition 9.4.4.

Let $A \in \mathbb{R}^{n \times n}$. Suppose A has a chain $\{v_1, v_2, \dots, v_k\}$ is of generalized e-vectors with e-value λ , meaning $(A - \lambda)v_1 = 0$ and $(A - \lambda)v_{k-1} = v_k$ for $k \geq 2$, then

1. $e^{tA}v_1 = e^{\lambda t}v_1$,
2. $e^{tA}v_2 = e^{\lambda t}(v_2 + tv_1)$,
3. $e^{tA}v_3 = e^{\lambda t}(v_3 + tv_2 + \frac{t^2}{2}v_1)$,
4. $e^{tA}v_k = e^{\lambda t}(v_k + tv_{k-1} + \dots + \frac{t^{k-1}}{(k-1)!}v_1)$.

Proof: Study the chain condition,

$$(A - \lambda I)v_2 = v_1 \Rightarrow (A - \lambda)^2 v_2 = (A - \lambda I)v_1 = 0$$

$$(A - \lambda I)v_3 = v_2 \Rightarrow (A - \lambda I)^2 v_3 = (A - \lambda I)v_2 = v_1$$

Continuing with such calculations⁴ we find $(A - \lambda I)^j v_i = v_{i-j}$ for all $i > j$ and $(A - \lambda I)^i v_i = 0$. The magic formula completes the proof:

$$e^{tA}v_2 = e^{\lambda t}(v_2 + t(A - \lambda I)v_2 + \frac{t^2}{2}(A - \lambda I)^2 v_2 \dots) = e^{\lambda t}(v_2 + tv_1)$$

likewise,

$$\begin{aligned} e^{tA}v_3 &= e^{\lambda t}(v_3 + t(A - \lambda I)v_3 + \frac{t^2}{2}(A - \lambda I)^2 v_3 + \frac{t^3}{3!}(A - \lambda I)^3 v_3 + \dots) \\ &= e^{\lambda t}(v_3 + tv_2 + \frac{t^2}{2}(A - \lambda I)v_2) \\ &= e^{\lambda t}(v_3 + tv_2 + \frac{t^2}{2}v_1). \end{aligned}$$

We already proved the e-vector case in the preceding proposition and the general case follows from essentially the same calculation. \square

We have all the theory we need to solve systems of homogeneous constant coefficient ODEs.

⁴keep in mind these conditions hold because of our current labling scheme, if we used a different indexing system then you'd have to think about how the chain conditions work out, to test your skill perhaps try to find the general solution for the system with the matrix from Example 7.4.14

Example 9.4.5. Recall Example 7.2.11 we found $A = \begin{bmatrix} 3 & 1 \\ 3 & 1 \end{bmatrix}$ had e-values $\lambda_1 = 0$ and $\lambda_2 = 4$ and corresponding e-vectors

$$\vec{u}_1 = \begin{bmatrix} 1 \\ -3 \end{bmatrix} \quad \text{and} \quad \vec{u}_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

thus we find the general solution to $\vec{x}' = A\vec{x}$ is simply,

$$\vec{x}(t) = c_1 \begin{bmatrix} 1 \\ -3 \end{bmatrix} + c_2 e^{4t} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

just to illustrate the terms: we have fundamental solution set and matrix:

$$\left\{ \begin{bmatrix} 1 \\ -3 \end{bmatrix}, \begin{bmatrix} e^{4t} \\ e^{4t} \end{bmatrix} \right\} \quad X = \begin{bmatrix} 1 & e^{4t} \\ -3 & e^{4t} \end{bmatrix}$$

Notice that a different choice of e-vector scaling would just end up adjusting the values of c_1, c_2 in the event an initial condition was given. This is why different choices of e-vectors still gives us the same general solution. It is the flexibility to change c_1, c_2 that allows us to fit any initial condition.

Example 9.4.6. We can modify Example 9.2.2 and propose a different model for a tiger/bunny system. Suppose x is the number of tigers and y is the number of rabbits then

$$\frac{dx}{dt} = x - 4y \quad \frac{dy}{dt} = -10x + 19y$$

is a model for the population growth of tigers and bunnies in some closed environment. Suppose that there is initially 2 tigers and 100 bunnies. **Find the populations of tigers and bunnies at time $t > 0$:**

Solution: notice that we must solve $\vec{x}' = A\vec{x}$ where $A = \begin{bmatrix} 1 & -4 \\ -10 & 19 \end{bmatrix}$ and $\vec{x}(0) = [2, 100]^T$. We can calculate the eigenvalues and corresponding eigenvectors:

$$\det(A - \lambda I) = 0 \Rightarrow \lambda_1 = -1, \lambda_2 = 21 \Rightarrow u_1 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}, u_2 = \begin{bmatrix} -1 \\ 5 \end{bmatrix}$$

Therefore, using Proposition 9.4.4, the general solution has the form:

$$\vec{x}(t) = c_1 e^{-t} \begin{bmatrix} 2 \\ 1 \end{bmatrix} + c_2 e^{21t} \begin{bmatrix} -1 \\ 5 \end{bmatrix}.$$

However, we also know that $\vec{x}(0) = [2, 100]^T$ hence

$$\begin{aligned} \begin{bmatrix} 2 \\ 100 \end{bmatrix} &= c_1 \begin{bmatrix} 2 \\ 1 \end{bmatrix} + c_2 \begin{bmatrix} -1 \\ 5 \end{bmatrix} \Rightarrow \begin{bmatrix} 2 \\ 100 \end{bmatrix} = \begin{bmatrix} 2 & -1 \\ 1 & 5 \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} \\ \Rightarrow \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} &= \frac{1}{11} \begin{bmatrix} 5 & 1 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} 2 \\ 100 \end{bmatrix} = \frac{1}{11} \begin{bmatrix} 110 \\ 198 \end{bmatrix} \end{aligned}$$

Finally, we find the vector-form of the solution to the given initial value problem:

$$\vec{x}(t) = 10e^{-t} \begin{bmatrix} 2 \\ 1 \end{bmatrix} + \frac{198}{11}e^{21t} \begin{bmatrix} -1 \\ 5 \end{bmatrix}$$

Which means that $x(t) = 20e^{-t} - \frac{198}{11}e^{21t}$ and $y(t) = 1020e^{-t} + 90e^{21t}$ are the number of tigers and bunnies respective at time t .

Notice that a different choice of e-vectors would have just made for a different choice of c_1, c_2 in the preceding example. Also, notice that when an initial condition is given there ought not be any undetermined coefficients in the final answer⁵.

Example 9.4.7. We found that in Example 7.2.13 the matrix $A = \begin{bmatrix} 0 & 0 & -4 \\ 2 & 4 & 2 \\ 2 & 0 & 6 \end{bmatrix}$ has e -values $\lambda_1 = \lambda_2 = 4$ and $\lambda_3 = 2$ with corresponding e -vectors

$$\vec{u}_1 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad \vec{u}_2 = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \quad \vec{u}_3 = \begin{bmatrix} -2 \\ 1 \\ 1 \end{bmatrix}$$

Hence, using Proposition 9.4.4 and Theorem 9.4.1 the general solution of $\frac{d\vec{x}}{dt} = A\vec{x}$ is simply:

$$\vec{x}(t) = c_1e^{4t}\vec{u}_1 + c_2e^{4t}\vec{u}_2 + c_3e^{2t}\vec{u}_3 = c_1e^{4t} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} + c_2e^{4t} \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} + c_3e^{2t} \begin{bmatrix} -2 \\ 1 \\ 1 \end{bmatrix}$$

Example 9.4.8. Find the general solution of $\frac{d\vec{x}}{dt} = A\vec{x}$ given that:

$$A = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

We analyzed this matrix in Example 7.4.14. We found a pair of chains of generalized e -vectors all with eigenvalue $\lambda = 1$ which satisfied the following conditions:

$$(A - I)\vec{u}_3 = \vec{u}_1, \quad (A - I)\vec{u}_1 = 0 \quad (A - I)\vec{u}_4 = \vec{u}_2, \quad (A - I)\vec{u}_2 = 0$$

In particular, $\vec{u}_j = e_j$ for $j = 1, 2, 3, 4$. We can use the magic formula to extract 4 solutions from the matrix exponential, by Proposition 9.4.4 we find:

$$\begin{aligned} \vec{x}_1 &= e^{At}\vec{u}_1 = e^te_1 = e^te_1 \\ \vec{x}_2 &= e^{At}\vec{u}_2 = e^t(e_2 + te_1) \\ \vec{x}_3 &= e^{At}\vec{u}_3 = e^te_3 \\ \vec{x}_4 &= e^{At}\vec{u}_4 = e^t(e_4 + te_3) \end{aligned} \tag{9.2}$$

⁵Assuming of course that there are enough initial conditions given to pick a unique solution from the family of solutions which we call the "general solution".

Let's write the general solution in vector and scalar form, by Theorem 9.4.1,

$$\vec{x}(t) = c_1\vec{x}_1 + c_2\vec{x}_2 + c_3\vec{x}_3 + c_4\vec{x}_4 = c_1e^te_1 + c_2e^t(e_2 + te_1) + c_3e^te_3 + c_4e^t(e_4 + te_3) = \begin{bmatrix} c_1e^t + tc_2e^t \\ c_2e^t \\ c_3e^t + tc_4e^t \\ c_4e^t \end{bmatrix}$$

In other words, $x_1(t) = c_1e^t + tc_2e^t$, $x_2(t) = c_2e^t$, $x_3(t) = c_3e^t + tc_4e^t$ and $x_4(t) = c_4e^t$ form the general solution to the given system of differential equations.

Example 9.4.9. Find the general solution of $\frac{d\vec{x}}{dt} = A\vec{x}$ given (generalized)eigenvectors \vec{u}_i , $i = 1, 2, 3, 4, 5, 6, 7, 8, 9$ such that:

$$(A - I)\vec{u}_1 = 0, \quad A\vec{u}_2 = \vec{u}_2, \quad A\vec{u}_3 = 7\vec{u}_3, \quad (A - I)\vec{u}_4 = \vec{u}_1$$

$$(A + 5I)\vec{u}_5 = 0, \quad (A - 3I)\vec{u}_6 = \vec{u}_7, \quad A\vec{u}_7 = 3\vec{u}_7, \quad A\vec{u}_8 = 0, \quad (A - 3I)\vec{u}_9 = \vec{u}_6$$

We can use the magic formula to extract 9 solutions from the matrix exponential, by Proposition 9.4.4 we find:

$$\begin{aligned} \vec{x}_1 &= e^{At}\vec{u}_1 = e^t\vec{u}_1 = e^t\vec{u}_1 & (9.3) \\ \vec{x}_2 &= e^{At}\vec{u}_2 = e^t\vec{u}_2 \\ \vec{x}_3 &= e^{At}\vec{u}_3 = e^{7t}\vec{u}_3 \\ \vec{x}_4 &= e^{At}\vec{u}_4 = e^t(\vec{u}_4 + t\vec{u}_1) & \text{can you see why?} \\ \vec{x}_5 &= e^{At}\vec{u}_5 = e^{-5t}\vec{u}_5 \\ \vec{x}_6 &= e^{At}\vec{u}_6 = e^{3t}(\vec{u}_6 + t\vec{u}_7) & \text{can you see why?} \\ \vec{x}_7 &= e^{At}\vec{u}_7 = e^{3t}\vec{u}_7 \\ \vec{x}_8 &= e^{At}\vec{u}_8 = \vec{u}_8 \\ \vec{x}_9 &= e^{At}\vec{u}_9 = e^{3t}(\vec{u}_9 + t\vec{u}_6 + \frac{1}{2}t^2\vec{u}_7) & \text{can you see why?} \end{aligned}$$

Let's write the general solution in vector and scalar form, by Theorem 9.4.1,

$$\vec{x}(t) = \sum_{i=1}^9 c_i\vec{x}_i$$

where the formulas for each solution \vec{x}_i was given above. If I was to give an explicit matrix A with the eigenvectors given above it would be a 9×9 matrix. **Challenge:** find the matrix exponential e^{At} in terms of the given (generalized)eigenvectors.

Hopefully the examples have helped the theory settle in by now. We have one last question to settle for systems of DEqns.

Theorem 9.4.10.

The nonhomogeneous case $\vec{x}' = A\vec{x} + \vec{f}$ the general solution is $\vec{x}(t) = X(t)c + \vec{x}_p(t)$ where X is a fundamental matrix for the corresponding homogeneous system and \vec{x}_p is a particular solution to the nonhomogeneous system. We can calculate $\vec{x}_p(t) = X(t) \int X^{-1} \vec{f} dt$.

Proof: suppose that $\vec{x}_p = X\vec{v}$ for X a fundamental matrix of $\vec{x}' = A\vec{x}$ and some vector of unknown functions \vec{v} . We seek conditions on \vec{v} which make \vec{x}_p satisfy $\vec{x}_p' = A\vec{x}_p + \vec{f}$. Consider,

$$(\vec{x}_p)' = (X\vec{v})' = X'\vec{v} + X\vec{v}' = AX\vec{v} + X\vec{v}'$$

But, $\vec{x}_p' = A\vec{x}_p + \vec{f} = AX\vec{v} + \vec{f}$ hence

$$X \frac{d\vec{v}}{dt} = \vec{f} \Rightarrow \frac{d\vec{v}}{dt} = X^{-1} \vec{f}$$

Integrate to find $\vec{v} = \int X^{-1} \vec{f} dt$ therefore $x_p(t) = X(t) \int X^{-1} \vec{f} dt$. \square

If you ever work through variation of parameters for higher order ODEs then you should appreciate the calculation above. In fact, we can derive n -th order variation of parameters from converting the n -th order ODE by reduction of order to a system of n first order linear ODEs. You can show that the so-called Wronskian of the fundamental solution set is precisely the determinant of the fundamental matrix for the system $\vec{x}' = A\vec{x}$ where A is the companion matrix. I have this worked out in an old test from a DE course I taught at NCSU⁶

Example 9.4.11. Suppose that $A = \begin{bmatrix} 3 & 1 \\ 3 & 1 \end{bmatrix}$ and $\vec{f} = \begin{bmatrix} e^t \\ e^{-t} \end{bmatrix}$, find the general solution of the nonhomogeneous DE $\vec{x}' = A\vec{x} + \vec{f}$. Recall that in Example 9.4.5 we found $\vec{x}' = A\vec{x}$ has fundamental matrix $X = \begin{bmatrix} 1 & e^{4t} \\ -3 & e^{4t} \end{bmatrix}$. Use variation of parameters for systems of ODEs to construct \vec{x}_p . First calculate the inverse of the fundamental matrix, for a 2×2 we know a formula:

$$X^{-1}(t) = \frac{1}{e^{4t} - (-3)e^{4t}} \begin{bmatrix} e^{4t} & -e^{4t} \\ 3 & 1 \end{bmatrix} = \frac{1}{4} \begin{bmatrix} 1 & -1 \\ 3e^{-4t} & e^{-4t} \end{bmatrix}$$

⁶see solution of Problem 6 in www.supermath.info/ma341f07test2_sol.pdf for the $n = 2$ case of this comment, also §6.4 of Nagel Saff and Snider covers n -th order variation of parameters if you want to see details

Thus,

$$\begin{aligned}
 x_p(t) &= X(t) \int \frac{1}{4} \begin{bmatrix} 1 & -1 \\ 3e^{-4t} & e^{-4t} \end{bmatrix} \begin{bmatrix} e^t \\ e^{-t} \end{bmatrix} dt = \frac{1}{4} X(t) \int \begin{bmatrix} e^t - e^{-t} \\ 3e^{-3t} + e^{-5t} \end{bmatrix} dt \\
 &= \frac{1}{4} \begin{bmatrix} 1 & e^{4t} \\ -3 & e^{4t} \end{bmatrix} \begin{bmatrix} e^t + e^{-t} \\ -e^{-3t} - \frac{1}{5}e^{-5t} \end{bmatrix} \\
 &= \frac{1}{4} \begin{bmatrix} 1(e^t + e^{-t}) + e^{4t}(-e^{-3t} - \frac{1}{5}e^{-5t}) \\ -3(e^t + e^{-t}) + e^{4t}(-e^{-3t} - \frac{1}{5}e^{-5t}) \end{bmatrix} \\
 &= \frac{1}{4} \begin{bmatrix} e^t + e^{-t} - e^t - \frac{1}{5}e^{-t} \\ -3e^t - 3e^{-t} - e^t - \frac{1}{5}e^{-t} \end{bmatrix} \\
 &= \frac{1}{4} \begin{bmatrix} \frac{4}{5}e^{-t} \\ -4e^t - \frac{16}{5}e^{-t} \end{bmatrix}
 \end{aligned}$$

Therefore, the general solution is

$$\vec{x}(t) = c_1 \begin{bmatrix} 1 \\ -3 \end{bmatrix} + c_2 e^{4t} \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \frac{1}{5} \begin{bmatrix} e^{-t} \\ -e^t - 4e^{-t} \end{bmatrix}.$$

The general scalar solutions implicit within the general vector solution $\vec{x}(t) = [x(t), y(t)]^T$ are

$$x(t) = c_1 + c_2 e^{4t} + \frac{1}{5}e^{-t} \quad y(t) = -3c_1 + c_2 e^{4t} - \frac{1}{5}e^t - \frac{4}{5}e^{-t}.$$

I'll probably ask you to solve a 3×3 system in the homework. The calculation is nearly the same as the preceding example with the small inconvenience that finding the inverse of a 3×3 requires some calculation.

Remark 9.4.12.

You might wonder how would you solve a system of ODEs $x' = Ax$ such that the coefficients A_{ij} are not constant. We will not cover such problems in this course. We do cover how to solve an n -th order ODE with nonconstant coefficients via series techniques in Math 334. It's probably possible to extend some of those techniques to systems. Laplace Transforms also extend to systems of ODEs. It's just a matter of algebra. Nontrivial algebra.

9.5 solutions for systems of DEqns with complex eigenvalues

The calculations in the preceding section still make sense for a complex e-value and complex e-vector. However, we usually need to find real solutions. How to fix this? The same way as always. We extract real solutions from the complex solutions. Fortunately, our previous work on linear independence of complex e-vectors insures that the resulting solution set will be linearly independent.

Proposition 9.5.1.

Let $A \in \mathbb{R}^{n \times n}$. Suppose A has a chain $\{v_1, v_2, \dots, v_k\}$ is of generalized complex e-vectors with e-value $\lambda = \alpha + i\beta$, meaning $(A - \lambda)v_1 = 0$ and $(A - \lambda)v_{k-1} = v_k$ for $k \geq 2$ and $v_j = a_j + ib_j$ for $a_j, b_j \in \mathbb{R}^n$ for each j , then

1. $e^{tA}v_1 = e^{\lambda t}v_1$,
2. $e^{tA}v_2 = e^{\lambda t}(v_2 + tv_1)$,
3. $e^{tA}v_3 = e^{\lambda t}(v_3 + tv_2 + \frac{t^2}{2}v_1)$,
4. $e^{tA}v_k = e^{\lambda t}(v_k + tv_{k-1} + \dots + \frac{t^{k-1}}{(k-1)!}v_1)$.

Furthermore, the following are the $2k$ linearly independent real solutions that are implicit within the complex solutions above,

1. $x_1 = \operatorname{Re}(e^{tA}v_1) = e^{\alpha t}[(\cos \beta t)a_1 - (\sin \beta t)b_1]$,
2. $x_2 = \operatorname{Im}(e^{tA}v_1) = e^{\alpha t}[(\sin \beta t)a_1 + (\cos \beta t)b_1]$,
3. $x_3 = \operatorname{Re}(e^{tA}v_2) = e^{\alpha t}[(\cos \beta t)(a_2 + ta_1) - (\sin \beta t)(b_2 + tb_1)]$,
4. $x_4 = \operatorname{Im}(e^{tA}v_2) = e^{\alpha t}[(\sin \beta t)(a_2 + ta_1) + (\cos \beta t)(b_2 + tb_1)]$,
5. $x_5 = \operatorname{Re}(e^{tA}v_3) = e^{\alpha t}[(\cos \beta t)(a_3 + ta_2 + \frac{t^2}{2}a_1) - (\sin \beta t)(b_3 + tb_2 + \frac{t^2}{2}b_1)]$,
6. $x_6 = \operatorname{Im}(e^{tA}v_3) = e^{\alpha t}[(\sin \beta t)(a_3 + ta_2 + \frac{t^2}{2}a_1) + (\cos \beta t)(b_3 + tb_2 + \frac{t^2}{2}b_1)]$.

Proof: the magic formula calculations of the last section just as well apply to the complex case. Furthermore, we proved that

$$\operatorname{Re}[e^{\alpha t + i\beta t}(v + iw)] = e^{\alpha t}[(\cos \beta t)v - (\sin \beta t)w]$$

and

$$\operatorname{Im}[e^{\alpha t + i\beta t}(v + iw)] = e^{\alpha t}[(\sin \beta t)v + (\cos \beta t)w],$$

the proposition follows. \square

Example 9.5.2. This example uses the results derived in Example 7.7.2. Let $A = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$ and find the e -values and e -vectors of the matrix. Observe that $\det(A - \lambda I) = \lambda^2 + 1$ hence the eigenvalues are $\lambda = \pm i$. We find $u_1 = [1, i]^T$. Notice that

$$u_1 = \begin{bmatrix} 1 \\ i \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} + i \begin{bmatrix} 0 \\ 1 \end{bmatrix}.$$

This means that $\vec{x}' = A\vec{x}$ has general solution:

$$\vec{x}(t) = c_1 \left(\cos(t) \begin{bmatrix} 1 \\ 0 \end{bmatrix} - \sin(t) \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right) + c_2 \left(\sin(t) \begin{bmatrix} 1 \\ 0 \end{bmatrix} + \cos(t) \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right).$$

The solution above is the "vector-form of the solution". We can add the terms together to find the scalar solutions: denoting $\vec{x}(t) = [x(t), y(t)]^T$,

$$x(t) = c_1 \cos(t) + c_2 \sin(t) \quad y(t) = -c_1 \sin(t) + c_2 \cos(t)$$

These are the parametric equations of a circle with radius $R = \sqrt{c_1^2 + c_2^2}$.

Example 9.5.3. We solved the e -vector problem for $A = \begin{bmatrix} 1 & 1 & 0 \\ -1 & 1 & 0 \\ 0 & 0 & 3 \end{bmatrix}$ in Example 7.7.4. We found one real e -value $\lambda_1 = 3$ and a pair of complex e -values $\lambda_2 = 1 \pm i$. The corresponding e -vectors were:

$$\vec{u}_1 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \quad \vec{u}_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} + i \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

We identify that $\text{Re}(\vec{u}_2) = e_2$ and $\text{Im}(\vec{u}_2) = e_1$. The general solution of $\vec{x}' = A\vec{x}$ should have the form:

$$\vec{x}(t) = c_1 e^{At} \vec{u}_1 + c_2 \text{Re}(e^{At} \vec{u}_2) + c_3 \text{Im}(e^{At} \vec{u}_2)$$

The vectors above are e -vectors so these solution simplify nicely:

$$\vec{x}(t) = c_1 e^{3t} e_3 + c_2 e^t (\cos(t) e_2 - \sin(t) e_1) + c_3 e^t (\sin(t) e_2 + \cos(t) e_1)$$

For fun let's look at the scalar form of the solution. Denoting $\vec{x}(t) = [x(t), y(t), z(t)]^T$,

$$x(t) = -c_2 e^t \sin(t) + c_3 e^t \cos(t), \quad y(t) = c_2 e^t \cos(t) + c_3 e^t \sin(t), \quad z(t) = c_1 e^{3t}$$

Believe it or not this is a spiral helix which has an exponentially growing height and radius.

Example 9.5.4. Let's suppose we have a chain of 2 complex eigenvectors \vec{u}_1, \vec{u}_2 with eigenvalue $\lambda = 2 + i3$. I'm assuming that

$$(A - (2 + i)I)\vec{u}_2 = \vec{u}_1, \quad (A - (2 + i)I)\vec{u}_1 = 0.$$

We get a pair of complex-vector solutions (using the magic formula which truncates since these are *e*-vectors):

$$\vec{z}_1(t) = e^{At}\vec{u}_1 = e^{(2+i)t}\vec{u}_1, \quad \vec{z}_2(t) = e^{At}\vec{u}_2 = e^{(2+i)t}(\vec{u}_2 + t\vec{u}_1),$$

The real and imaginary parts of these solutions give us 4 real solutions which form the general solution:

$$\begin{aligned} \vec{x}(t) = & c_1 e^{2t} [\cos(3t) \operatorname{Re}(\vec{u}_1) - \sin(3t) \operatorname{Im}(\vec{u}_1)] \\ & + c_2 e^{2t} [\sin(3t) \operatorname{Re}(\vec{u}_1) + \cos(3t) \operatorname{Im}(\vec{u}_1)] \\ & + c_3 e^{2t} [\cos(3t) [\operatorname{Re}(\vec{u}_2) + t \operatorname{Re}(\vec{u}_1)] - \sin(3t) [\operatorname{Im}(\vec{u}_2) + t \operatorname{Im}(\vec{u}_1)]] \\ & + c_4 e^{2t} [\sin(3t) [\operatorname{Re}(\vec{u}_2) + t \operatorname{Re}(\vec{u}_1)] + \cos(3t) [\operatorname{Im}(\vec{u}_2) + t \operatorname{Im}(\vec{u}_1)]] . \end{aligned}$$

9.6 geometry and difference equations revisited

In Example 7.1.5 we studied $A = \begin{bmatrix} 3 & 0 \\ 8 & -1 \end{bmatrix}$ and how it pushed the point $x_o = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$ around the plane. We found x_i for $i = 1, 2, 3, 4$ by multiplication by A directly. That method is fine for small i but what if we wished to know the formula for the 1000-th state? We should hope there is some way to find that state without direct multiplication repeated 1000 times. One method is to make use of the diagonalization of the matrix. We know that *e*-vectors (if they exist) can be glued together to make the diagonalizing similarity transforming matrix; there exists $P \in \mathbb{R}^{n \times n}$ such that $P^{-1}AP = D$ where D is a diagonal matrix. Notice that D^k is easy to calculate. We can solve for $A = PDP^{-1}$ and find that $A^2 = PDP^{-1}PDP^{-1} = PD^2P^{-1}$. Then you can prove inductively that $A^k = PD^kP^{-1}$. It is much easier to calculate PD^kP^{-1} when $k \gg 1$.

9.6.1 difference equations vs. differential equations

I mentioned that the equation $x_{k+1} = Ax_k$ is a *difference equation*. We can think of this as a differential equation where the time-step is always one-unit. To see this I should remind you how $\vec{x}' = B\vec{x}$ is defined in terms of a limiting process:

$$\vec{x}'(t) = \lim_{h \rightarrow 0} \frac{\vec{x}(t+h) - \vec{x}(t)}{h} = B\vec{x}(t)$$

A gross approximation to the continuous limiting process would be to just take $h = 1$ and drop the limit. That approximation yields:

$$B\vec{x}(t) = \vec{x}(t+1) - \vec{x}(t).$$

We then suppose $t \in \mathbb{N}$ and denote $\vec{x}(t) = \vec{x}_t$ to obtain:

$$\vec{x}_{t+1} = (B + I)\vec{x}_t.$$

We see that the differential equation $\vec{x}' = B\vec{x}$ is crudely approximated by the difference equation $\vec{x}_{t+1} = A\vec{x}_t$, where $A = B + I$. Since we now have tools to solve differential equations directly it should be interesting to contrast the motion generated by the difference equation to the exact parametric equations which follow from the e-vector solution of the corresponding differential equation.

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